Rating Based CDS Curves

Olga Kolokolova, Ming-Tsung Lin, Ser-Huang Poon*

December 21, 2016

Abstract

In this paper, we explore the extent to which term structure of individual CDS spreads can be explained by the firm's rating. Using the Nelson-Siegel model, we construct, for each day, CDS curves from a *cross section* of CDS spreads for each rating class. We find that the fitted CDS curves contain meaningful information in the sense that 76% of their time-series variations can be explained by the typical credit and liquidity factors that are known to drive CDS spreads. The residuals, on the other hand, contain mostly transient liquidity information. Moreover, deviations from the curve tend to disappear and CDS spreads converge towards the fitted curves over time; the *larger* is the deviation, the *more likely* is the convergence. Trading strategies exploiting the convergence of deviations could potentially generate an average return of 3.6% (5 days holding period) and 9% (20 days holding period). Our findings suggest that our CDS curves contain the core credit and liquidity information, which could be used to price other CDSs of the same rating class. This is important in credit risk management where the CDS spreads of a wide spectrum of ratings and term structure are needed for evaluating counterparty risk.

Key Words: Credit Default Swap (CDS), Trading Strategy, CDS Term Structure, Credit Rating.

JEL: G11, G17, G24

*Ming-Tsung Lin (corresponding author; ming-tsung.lin@dmu.ac.uk) is at De Montfort University. Olga Kolokolova (olga.kolokolova@manchester.ac.uk) and Ser-Huang Poon (ser-huang.poon@manchester.ac.uk) are at the University of Manchester.

Rating Based CDS Curves

Abstract

In this paper, we explore the extent to which term structure of individual CDS spreads can be explained by the firm's rating. Using the Nelson-Siegel model, we construct, for each day, CDS curves from a *cross section* of CDS spreads for each rating class. We find that the fitted CDS curves contain meaningful information in the sense that 76% of their time-series variations can be explained by the typical credit and liquidity factors that are known to drive CDS spreads. The residuals, on the other hand, contain mostly transient liquidity information. Moreover, deviations from the curve tend to disappear and CDS spreads converge towards the fitted curves over time; the *larger* is the deviation, the *more likely* is the convergence. Trading strategies exploiting the convergence of deviations could potentially generate an average return of 3.6% (5 days holding period) and 9% (20 days holding period). Our findings suggest that our CDS curves contain the core credit and liquidity information, which could be used to price other CDSs of the same rating class. This is important in credit risk management where the CDS spreads of a wide spectrum of ratings and term structure are needed for evaluating counterparty risk.

Key Words: Credit Default Swap (CDS), Trading Strategy, CDS Term Structure, Credit Rating.

JEL: G11, G17, G24

1 Introduction

Identifying the determinants of CDS (Credit Default Swap) spreads is a central question in many CDS studies. In addition to Merton (1974)'s and Leland and Toft (1996)'s fundamentals of the default risk, recent studies find that CDS spreads are driven by many other factors apart from credit risk. This paper focuses on the information contained in the cross section of CDS spreads at the rating class level. Although the use of a credit or rating curve is a common industrial practice,[1] we are the first, to the best of our knowledge, to study the rating-based CDS curves[2] and their features: we use the Nelson and Siegel (1987) model to extract the rating-based hazard rates from CDS spreads, and investigate the characteristics of the information content and time-series properties of the fitted values and the residuals. We find that the fitted curve captures both firm-specific and market credit and liquidity information, producing a high R-square in the pooled sample regression. This finding suggests that our rating-based CDS curves are good representation of the cross section of CDS spreads, and hence a good benchmark for pricing other CDS of the same rating. Next, we focus on the residuals of the Nelson-Siegel fitted curves. Using the error correction model (ECM), we find that these residuals move in the opposite direction to the time-series changes of the CDS spreads, suggesting that these deviations will disappear and CDS spread converges to the fitted curve over time. All together, our findings suggest that the residuals are transient and are due to short-term illiquidity, while the fitted curves are persistent and are more related to the fundamental CDS risks.

Further investigation reveals that the speed of which CDS spread converges to the fitted curve is related to the magnitude of the deviation between the actual CDS spread and the fitted curve. We sort the CDSs into five portfolios based on the relative size of the deviations, and find evidence that the larger the deviation is, the more likely is the convergence. A trading strategy that consists of a long position in the portfolio of CDSs with the *most negative* deviations and a short position in the portfolio of CDSs with the *most positive* deviations produces statistically

[1]For instance, GFI/FENICS constructs single-name CDS spreads using Hull-White methodology; Markit also provides various smoothed credit curves (such as single-name CDS curves and sector credit curves) by pair-wise interpolating the individual CDS spreads. See Markit (2012) user manual for more information. In practice, credit curve is often used for clients to analyze the delta risk of the CDS spreads (CV01) or to assess the CDS spreads for other tenors. Credit curve providers might not consider the term structure of the CDS spreads, or provide the accuracy test for these curves.

[2]In this paper, rating information is provided by the rating agencies (i.e. S&P and Moody's). The rating by these rating agencies is accepted widely and is available publicly. We do not construct our own ratings implied by the CDS spreads.

significant positive returns for 5 and 20 days holding period. These results indirectly confirm the time-series convergence of the CDS spreads to our rating-based CDS curves.

Our study contributes to the strand of literature that studies the determinants of CDS spreads. Das, Hanouna, and Sarin (2009) find that both accounting-based and market-based credit information are important drivers of CDS spreads. In addition to credit risk, several studies find that CDS illiquidity increases CDS spreads. Tang and Yan (2007) find several liquidity measures derived from CDS trading information such as total number of quotes and trades and trade-to-quote ratio have significant impact on CDS spreads. Corò, Dufour, and Varotto (2013) use the bid-ask spreads of intra-day trades to construct a sector liquidity factor, and find this sector liquidity factor dominates the other credit factors in driving CDS spreads. Das and Hanouna (2009) further establish the linkage between equity liquidity and CDS spreads.

More recently, systematic risk was found to be priced in CDS spreads. Longstaff, Pan, Pedersen, and Singleton (2011) find that global factors are more important than individual country factors in driving CDS spreads. Doshi, Ericsson, Jacobs, and Turnbull (2013) find that variables reflecting market conditions, such as the 6-month Treasury yield and the difference between the 10-year and 6-month yields, can explain the cross-sectional CDS variations. Similarly, Tang and Yan (2013) study CDS transaction data and find both firm and market fundamental variables are the most significant drivers of CDS spreads. Moreover, they find CDS spreads are more sensitive to macro variables such as VIX, especially during the crisis period. Conrad, Dittmar, and Hameed (2011) find changes of CDS spreads of systematically important financial institutions lead changes of CDS spreads of the other firms. Galil, Shapir, Amiram, and Ben-Zion (2014) find median CDS spreads of mixed credit quality have a cross-sectional explanatory power for individual CDS spreads. Last but not least, Lin, Kolokolova, and Poon (2016) construct various CDS systematic credit and liquidity factors, and find these systematic factors to have a higher explanatory power in the quarterly changes of 1-year CDS spreads than the firm-specific factors. They also find systematic liquidity became more pronounced from 2008 onwards.

Our study also relates to another strand of literature that concerns the relationship between credit rating and CDS spreads. Hull, Predescu, and White (2004) find that, among all types of rating announcements, only *Review on Downgrade* has an impact on CDS spreads.

Their findings suggest that CDS market is efficient and can anticipate most rating changes. Finnerty, Miller, and Chen (2013) also find evidence that CDS market can anticipate the announcements on the credit rating changes. On the other hand, Norden and Weber (2004) and Micu, Remolona, and Wooldridge (2006) conclude that all types of rating announcements have a significant impact on CDS spreads. All these studies suggest that CDS market is indeed linked to the credit ratings. Our study has a different focus. We do not study individual rating announcement (in which usually the impact within a short observation window is studied). In this paper, we investigate the CDS spreads at the rating level by constructing cross-sectional CDS curves and study the extent to which individual CDS spread variations can be explained by these curves. We demonstrate the economic substance of the CDS curves by providing evidence that deviations from the curves will disappear and CDS spreads converge towards the curves over time.

The rest of the paper is structured as follows: section 2 introduces the procedures for constructing the rating-based CDS curves using the Nelson-Siegel model, section 3 illustrates the goodness of fit of the Nelson-Siegel model, sections 4 and 5 test the convergence towards the CDS curves, section 6 discusses a trading strategy that exploits the pattern of convergence, section 7 studies the information content of the fitted CDS curves and the residuals, and section 8 concludes.

2 Constructing Rating-Based CDS Curves

In this section, we detail the Nelson-Siegel model and explain how it is used to produce the rating-based CDS curves. The Nelson-Siegel model is a popular model for fitting the interest rate yield curve. First, we explain how the CDS-implied hazard rate is calculated from CDS spread. CDS represents an insurance to protect CDS buyers against any loss due to the firm's default. In a CDS contract, protection sellers compensate protection buyers' the amount lost due to a credit event (e.g. default). In return, protection buyers pay periodic premiums to protection sellers during the protection periods up to the credit event. Hence, the pricing of a CDS contract has two parts: the protection part and the premium part.

Assume that there are N payments in a CDS contract,[3] and that default takes place only immediately after the premium is paid such that there is no accrual at default. If the market discount rate (r) and firm's hazard rate (h) are time-varying, then the expected present values of the protection and premium parts can be expressed as (given the information filtration at time t):

$$PV_{\text{Protection}} = \mathbb{E}\left[\sum_{i=1}^{N} \exp\left(-\int_t^{t_i} r_u du\right)\ \exp\left(-\int_t^{t_i} h_u du\right) (1-R)\ h_{t_i}\ \Delta t_i \middle| \mathcal{F}_t\right] \tag{1}$$

$$PV_{\text{Premium}} = \mathbb{E}\left[\sum_{i=1}^{N} \exp\left(-\int_t^{t_i} r_u du\right)\ \exp\left(-\int_t^{t_i} h_u du\right) k\ \Delta t_i \middle| \mathcal{F}_t\right] \tag{2}$$

where Δt_i is the time period between payments, R is the recovery rate of the underlying CDS and k is the premium (i.e. CDS spreads) paid by the protection buyer to the protection seller. The fair price of the CDS spread (k) is determined when the two expected present values are the same. Our aim is to obtain h_u implied by the observed CDS spread.

For each CDS spread of a particular maturity, τ, we assume a flat term structure for the market discount rate and the hazard rate such that $r_u = r$ and $h_u = h$.[4] Then, under no-arbitrage,

$$e^{-r(t_i-t)}\ e^{-h(t_i-t)}\ (1-R)\ h\ \Delta t_i = e^{-r(t_i-t)}\ e^{-h(t_i-t)}\ k\ \Delta t_i,\ \forall t_i. \tag{3}$$

Equation (3) implies that, given the recovery rate (R) and the CDS spread (k), the hazard rate h implied by a CDS spread is

$$h = \frac{k}{1-R}. \tag{4}$$

Since each CDS contract has a time to maturity, thus the CDS-implied hazard rate h of firm i at time t with CDS maturity τ is expressed by $h_{i,t,\tau} = \frac{k_{i,t,\tau}}{1-R_{i,t}}$. R is usually set equal to 0.4, but, in this paper, we use the reported recovery rate in Markit. Markit requires the data

[3] In this case, the N payment periods are $[t, t_1], [t_1, t_2], ..., [t_{N-1}, t_N]$.

[4] Several studies have used similar assumptions; see Carr and Wu (2011) among others. We do allow CDS spreads of different maturities to have different hazard rates.

providers to report the quote for CDS spreads and the corresponding recovery rate. Markit provides the recovery rate at the individual entity level. Next, we link hazard rate to firm's average rating which is also provided by Markit. Markit calculates firm's average rating as the average of the Moody's and S&P ratings adjusted to the seniority of the CDS and rounded to not include the '+' and '-' levels. Rating provides information about the comparative default risk across rating classes, assuming that all entities in the same rating class will have the same default rate. Next we decompose the implied hazard rate $h_{i,t,\tau}$ in Equation (4) into:

$$h_{i,t,\tau} = y_{r,t,\tau} + e_{i,t,\tau}, \tag{5}$$

where $y_{r,t,\tau}$ is the hazard rate specific to rating class r on day t for maturity τ, and e is the firm-specific residual. $y_{r,t,\tau}$ is time-varying and maturity dependent, but the same for all firms in the same rating class; y captures the systematic rating class information, while e represents the firm's idiosyncratic information and noise. Empirically, we use the Nelson-Siegel model with a hump-shaped term structure as shown below to estimate $y(\tau)$ for each rating class r on day t:[5]

$$\begin{aligned} y(\tau|\beta_0, \beta_1, \beta_2, m) = \beta_0 + \beta_1 &\left(\frac{1 - \exp(-\tau/m)}{\tau/m} \right) \\ + \beta_2 &\left(\frac{1 - \exp(-\tau/m)}{\tau/m} - \exp(-\tau/m) \right) \end{aligned} \tag{6}$$

where β_0 and β_1 are the long-term and short-term hazard rates, β_2 captures a possible hump at the medium term, and m determines the shape and the timing of the hump. We set $\beta_0 > 0$, $\beta_0 + \beta_1 > 0$, $\beta_0 + \beta_1 + \beta_2 > 0$ and $m > 0$ to avoid negative $y(\tau)$. In addition, since some CDS contracts are more liquid than others, we allocate more weights for the liquid CDS contracts. Specifically, we give the 5-year CDSs a weight of 3, the 1-year and 2-year CDSs a weight of 2, and the other CDSs a weight of 1. The estimation is performed for each observation date t, using all CDSs of the same rating r on that day. Since $y(\tau)$ is fitted to a group of CDSs with the same rating, $y(\tau)$ will be the same for all CDSs that have the same maturity and the same rating. Notably, the rating information in our sample is obtained from Moody's and

[5] The proposed model here is consistent with a constant hazard rate for each CDS of maturity τ. While $h(\tau) = k(\tau)/[1 - R]$ represents the "spot" default rate implied by CDS spread of maturity τ, the Nelson-Siegel model is used here to fit the shape of the term structure of these spot rates.

S&P via Markit. The rating provided by rating agencies does not change as frequently as CDS spread. Therefore, it is often seen that some CDS spreads with better rating are higher than some CDS spreads with poor rating, leading to potential crossing of the estimated curves. Also, the shape of our fitted curves may also reflect the preference between short-term and long-term CDS contracts. For the aforementioned reasons, we do not impose any restrictions on the relationship between CDS curves.

3 Fitted CDS Curves

The Nelson-Siegel model is fitted using all CDS spreads of the same rating class for a particular day. This process is repeated for each rating class and for each day in our sample period. Here, we show the fitting results for 23 December 2008 as an illustration. All the CDS spreads are collected from Markit database for U.S. firms that are written on their senior unsecured debts. Our CDS sample is from May 2002 to May 2012. We exclude CDS with default rating because there are too few observations, not enough for an adequate Nelson-Siegel fit. The time to maturity of the CDSs ranges from 6 months to 10 years.[6] The descriptive statistics of our entire sample and the CDSs quoted on 23 December 2008 are reported in Table 1. Panel A reports the descriptive statistics of the entire CDS samples. Our CDS sample includes more than 3.6 million observations. The average CDS spread is 151 bps, with the maximum of more than 20,000 bps and the minimum of just 0.6 bps. The extraordinarily large spread is due to the procedure used to annualize CDS spreads. Normally, the CDS spread should be within 10,000 bps; otherwise, the CDS buyers pay more than the nominal of the CDS contract. However, if firm's default is expected to happen within one year, the premium payment during a protection period is close to 10,000 bps, leading the annualized CDS spread exceeds 10,000 bps.[7] When we break down our sample into groups by time to maturity, the 5-year CDS has the largest number of observations (544 thousand observations) while 6-month CDS has the smallest number of observations (308 thousand observations). We also observe that the sample average CDS spread increases with the length of time to maturity; 6-month CDSs have the smallest sample average

[6]The times to maturity of the CDSs in Markit are 6 months, 1, 2, 3, 4, 5, 7, 10, 15, 20, and 30 years. We select the CDSs with time to maturity 10 years or less, because these CDSs are traded more frequently.

[7]See, Hull, Predescu, and White (2004), for further explanation.

of 94 bps, while 10-year CDSs have the largest average of 187 bps. The maximum CDS spread in our CDS sample is 24,559 bps. Panel B reports the descriptive statistics of the CDSs on 23 December 2008, according to rating class. We find the average CDS spreads for different ratings increase monotonically from the best rating (115 bps for AAA) to the worst rating (2611 bps for C). With 1,343 observations, BBB rating has the largest number of observations; with just 15 observations, AAA rating has the smallest number of observations.

Figure 1 shows the estimation results for 23 December 2008. We note from Figure 1 that fitted CDS curves do not cross, and the fitted values are consistent with the order of the ratings. The best rating, AAA, is at the bottom, while the worst rating, C, is at the top, meaning that CDS-implied hazard rates for firms with the best rating are the lowest, and the implied hazard rates for the firms with the worst rating are the highest. Furthermore, the CDS curves of the investment grades are flatter than those for the junk grades, suggesting a stable and constant outlook for the investment grade firms. In contrast, with the convex curve for the junk grade firms, the CDS market appears to be more concern about the short-term solvency of the poor-rating firms.

However, one should note that, apart from the rating, the fitted curves are also affected by the number of observations. Since we have fewer observations for firms of the worst and the best ratings, the shapes of these fitted curves might be driven by outliers. Figure 2 plots the fitted curves and the actual CDS spreads for each rating class on 23 December 2008. In general, the Nelson-Siegel model captures the shapes of the curves well. For some ratings, e.g. AAA, where there are only few observations, the fitted curve just smooths over the observations. Where there are more observations, e.g. BBB, the curve reflects the main trends.

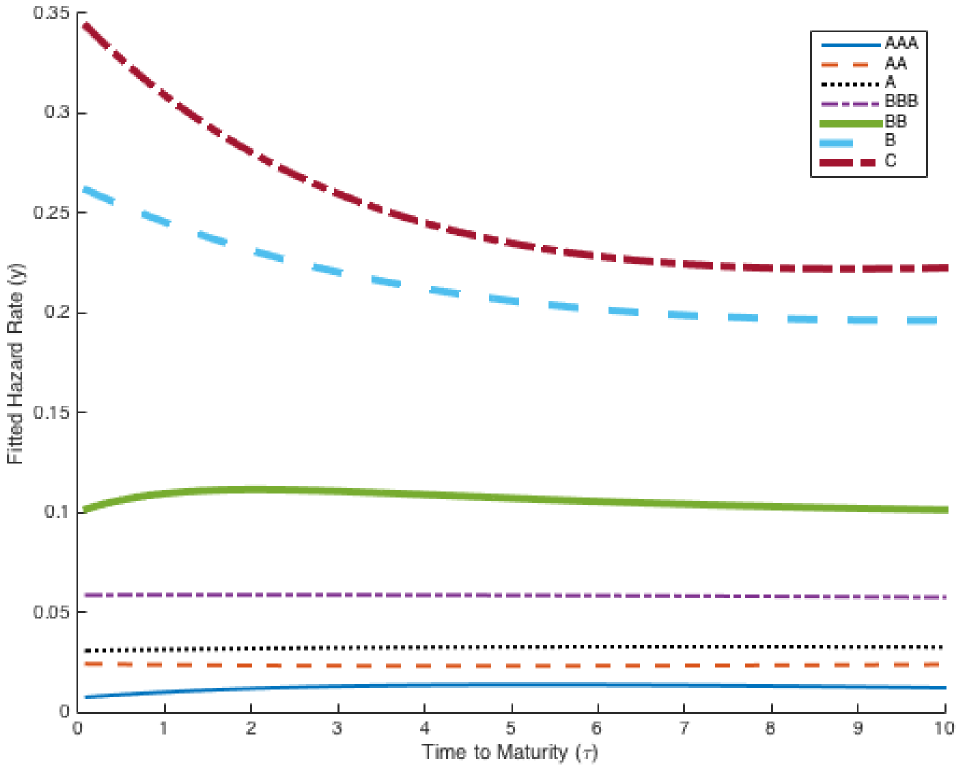
Next, we investigate the extent to which the individual CDS spreads can be explained by the rating-based hazard rates and the residuals. Our model specification shows a linear relationship between the individual CDS spreads and the two Nelson-Siegel components;[8] therefore, a pooled panel regression is used to examine the contributions of each component in explaining the CDS spread variations. Table 2 reports the regression of individual CDS spreads on the Nelson-Siegel components, y and e. Panel A reports the descriptive statistics of the components. The

[8] According to Equation (4) and (5), $CDSSpr_{i,t,\tau} = (1 - R_{i,t}) \times (y_{r_i,t,\tau} + e_{i,t,\tau})$, where $R_{i,t}$ is the Markit reported recovery rate for entity i.

Figure 1: Rating-Based CDS Curves and Parameter Values for 23 December 2008

This figure plots the rating-based CDS curves fitted using the Nelson-Siegel model below:

$$y(\tau|\beta_0, \beta_1, \beta_2, m) = \beta_0 + \beta_1 \left(\frac{1 - \exp(-\tau/m)}{\tau/m} \right) + \beta_2 \left(\frac{1 - \exp(-\tau/m)}{\tau/m} - \exp(-\tau/m) \right)$$

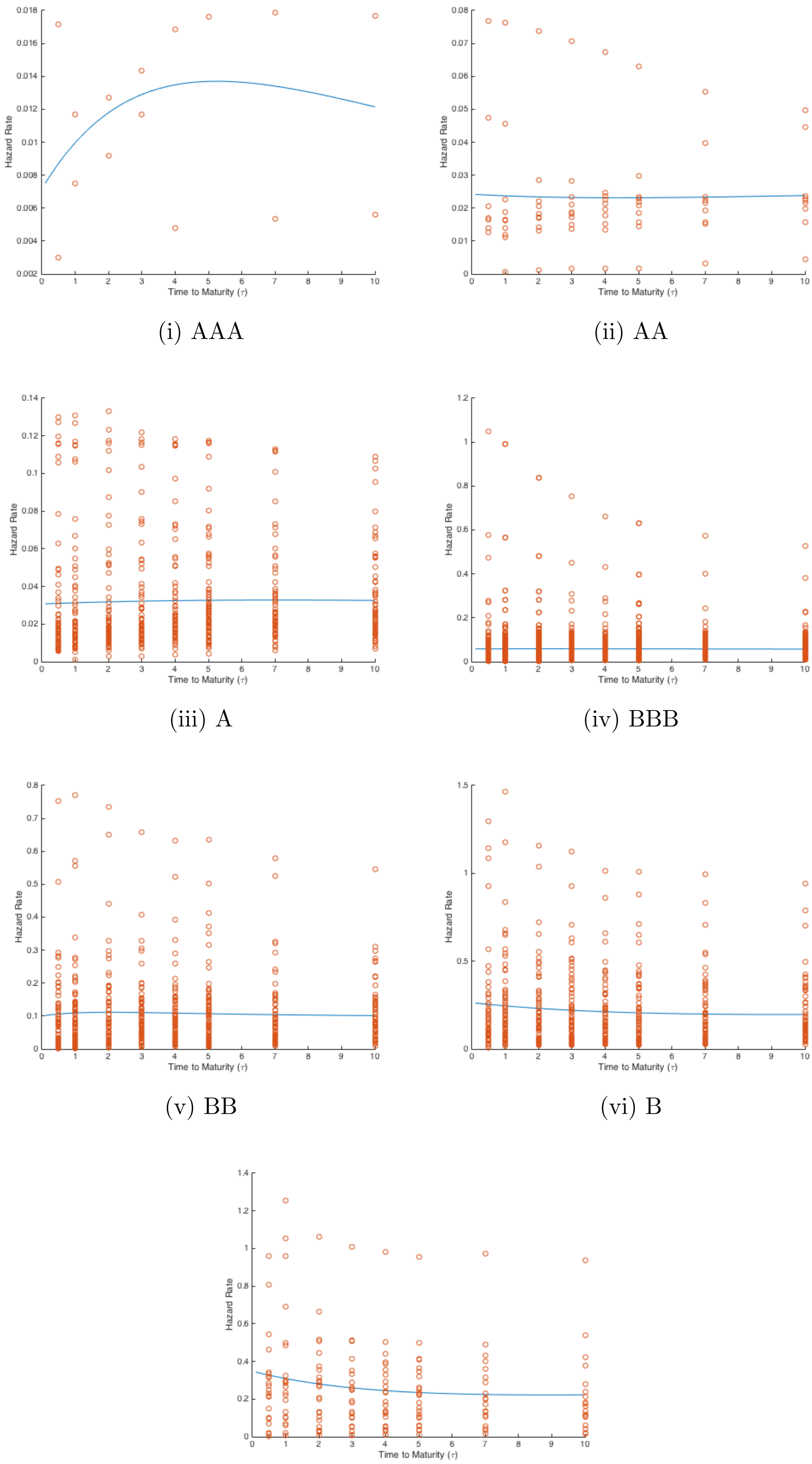


Model Parameters for Each Rating Class

	AAA	AA	A	BBB	BB	B	C
β_0	0.000	0.030	0.014	0.042	0.094	0.285	0.308
β_1	0.007	-0.006	0.017	0.017	0.006	-0.022	0.040
β_2	0.034	-0.012	0.031	0.019	0.048	-0.263	-0.348
m	3.913	5.176	9.849	9.871	1.363	5.950	4.319

Figure 2: Rating-Based CDS Curves for 23 December 2008

This figure plots the rating-based CDS curves, $y(\tau)$, fitted using the Nelson-Siegel model for each rating class. The symbol 'o' denotes the actual CDS-implied hazard rate (h).



(i) AAA

(ii) AA

(iii) A

(iv) BBB

(v) BB

(vi) B

(vii) C

average fitted value, y, is 288 bps with the maximum of 6,275 bps and the minimum of 2 bps. The average residual, e, is -47 bps with the maximum 22,223 bps and the minimum of -4,646 bps. Although y and e have similar standard deviation, the residual is more volatile in the sense that the residual varies up to 7.26 times (= 341bps/47bps) of its mean, while the fitted value varies up to 1.23 times (= 353bps/288bps) of its mean. Panel B reports the regression results. Model 1 and 2 are the results for the two components. We do not include section and year-month dummies in Model 1, but include these dummies in Model 2. All coefficients are significantly positive, with the adjusted R-square being more than 95%. Model 3 and 5 report the regression results using only one of the components. Again, the coefficients are significantly positive, with the adjusted R-square being approximately 40%. We also control for time fixed-effect and industry fixed-effect. After controlling these two effects in Model 4 and 6, we find that the results remain qualitatively the same, but a much higher explanatory power for the residual e (Model 6). In short, the signs of the regressive coefficients are rather expected, and the adjusted R-squares for the individual components are high. These findings suggest that Nelson-Siegel model provides a good fit, and show that both rating-based hazard rate (y) and residual (e) can explain CDS spread variations.

Table 1: CDS Descriptive Statistics

This table reports descriptive statistics for the sample CDS spreads according to their times to maturity, including sample mean (in basis points), standard deviation, maximum, minimum, and the number of observations. Panel A is for all CDS spreads from May 2002 to May 2012. Panel B is for CDS spreads on 23 December 2008 only. Normally, the CDS spread should be within 10,000 bps. However, if firm's default is expected to happen within one year, the premium payment during a protection period is close to 10,000 bps, leading the annualized CDS spread exceeds 10,000 bps.

Panel A: Full Sample Period

	All	6M	1Y	2Y	3Y	4Y	5Y	7Y	10Y
Mean	150.508	93.501	109.647	126.229	143.168	169.986	173.648	179.165	186.545
Std	314.291	311.063	358.899	336.067	312.236	340.501	296.330	283.211	266.024
Max	24,559.170	14,652.768	24,559.170	11,462.293	10,637.096	10,120.712	10,291.380	9,980.417	9,643.897
Min	0.600	0.600	0.814	0.791	1.276	1.451	2.327	3.272	4.337
Obs	3,658,096	308,245	468,378	471,722	506,898	359,003	544,392	504,271	495,187

Panel B: As of 23 December 2008

	AAA	AA	A	BBB	BB	B	C
Mean	115.31	235.66	321.39	584.33	1073.40	2205.00	2611.52
Std	53.24	171.18	288.16	797.32	1143.41	2194.69	2375.32
Max	178.60	767.45	1329.73	10473.06	7718.58	14633.96	12554.74
Min	29.94	6.34	12.79	17.37	19.00	93.33	30.61
Obs	15	79	571	1343	587	525	184

Table 2: Panel Regression of CDS Spread on Rating-based Hazard Rate (y) and residual (e)

This table reports the results of CDS spreads on the two Nelson-Siegel fitted components, y and e. Panel A reports the descriptive statistics for the components and Panel B reports the regression

$$CDSSpr_{i,t,\tau} = \beta_0 + \beta_1 y_{r_i,t,\tau} + \beta_2 e_{i,t,\tau} + \varepsilon_{i,t,\tau}$$

where $CDSSpr$ is the individual CDS spreads, y is the rating-based hazard rate, and e is the Nelson-Siegel residual. t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels. There are 3,658,096 observations in total. The sample period is from May 2002 to May 2012.

Panel A: Descriptive Statistics

	Mean	Std	Max	Min
Fitted Value y (bp)	288.264	353.148	6,274.906	1.635
Residual e (bp)	-47.210	340.754	22,223.418	-4,646.191

Panel B: Regression Results

	Dependent = $CDSSpr$					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.001***	-0.003***	-0.001***	0.002***	0.018***	0.015***
	[-353.32]	[-46.92]	[-46.42]	[5.76]	[1374.47]	[58.03]
y	0.688***	0.690***	0.549***	0.555***		
	[7850.55]	[6831.96]	[1499.08]	[1305.11]		
e	0.720***	0.721***			0.578***	0.617***
	[7929.44]	[7947.78]			[1536.17]	[1860.08]
Firm Section Dummies	No	Yes	No	Yes	No	Yes
Year-Month Dummies	No	Yes	No	Yes	No	Yes
Adj-R Square	0.97	0.97	0.38	0.39	0.39	0.54

4 Test on Fitted Curves and CDS Convergence

In order to assess the importance of the CDS curves fitted in the previous section, we test if the residuals are transient. To achieve this, we use the error correction model (ECM) to examine if the residuals reduce across time so that the individual CDS-implied hazard rates converge towards rating-based hazard rates. Specifically, we run the panel ECM regression below, using the actual CDS spread instead of the equivalent hazard rate:

$$\Delta CDSSpr_{i,t,\tau} = \beta_0 + \beta_1 \, \Delta y_{r_i,t,\tau} + \beta_2 \, e_{i,t-j,\tau} + \eta_{i,t,\tau} \tag{7}$$

where Δ is the time difference between time t and time $t-j$. We consider the weekly and monthly difference in our ECM regression (i.e. $j = 5$ and $j = 20$ trading days). $y_{r_i,t,\tau}$ is the relevant CDS curve for firm i and CDS maturity τ at the corresponding rating r. We use Δy to control for the core CDS characteristics, since y contains persistence rating class information. We also use the underlying sector and year-month dummies, respectively, to control for fixed effects.[9] A negative β_2 indicates that the component e is transient, and that the rating-based information fully captures the changes in individual CDS spreads.

Table 3 reports the panel ECM results. Model 1 reports the results for one week changes and Model 2 reports the results for one month changes. All the loadings on $\Delta y_{r_i,t,\tau}$ and $e_{i,t-j,\tau}$ are significant at the 1% level. We observe significant positive loadings on $\Delta y_{r_i,t,\tau}$, indicating that times-series movement of the fitted CDS curve can explain the movement of the individual CDS spreads. The finding provides some supports to the theoretical model of Cespa and Foucault (2014), in that individual CDS spread is affected by other CDS spreads of the same class via a cross-learning mechanism. Interestingly, we observe negative loadings on $e_{i,t-j,\tau}$, statistically significant at the 1% level for both 5- and 20-day differences. The result here means that the residual has a negative relationship with the time-series movement of the individual CDS spreads; the CDS spread will increase to correct for a negative residual, and vice versa for a positive residual. This finding supports our previous conjecture regarding the idiosyncratic information and noise in individual CDS spreads.

[9]Because of the software limit, we do not use firm and trade-day dummies to control for the fixed effects. With these year-month and sector dummies, we can then overcome the computational constraint.

Table 3: Panel Error Correction Model and CDS Convergence Test

This table tests the CDS convergence using the error correction model. The sample period is from May 2002 to May 2012. Model 1 uses time difference of one week (5 trading days), and Model 2 uses time difference of one month (20 trading days). t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Dependent = $CDSSpr_{i,t,\tau}$	
	Model 1	Model 2
Constant	-0.000	-0.000
	[-0.48]	[-0.36]
$\Delta y_{r_i,t,\tau}$	0.201***	0.363***
	[327.81]	[484.29]
$e_{i,t-5,\tau}$	$\boxed{\text{-0.016***}}$	
	[-178.28]	
$e_{i,t-20,\tau}$		$\boxed{\text{-0.061***}}$
		[-336.48]
Firm Sector Dummies	Yes	Yes
Year-Month Dummies	Yes	Yes
Adj R-sqr	0.05	0.13
Obs	3,482,714	3,342,077

Table 4 reports the ECM results year by year over the sample period. We report only the loadings for $e_{i,t-j,\tau}$ to save space. Overall, we find consistently negative loadings on $e_{i,t-j,\tau}$ in almost every year with the exception of 2008, meaning that the individual CDS-implied hazard rates did not converge to the rating-based hazard rates for that year. Since 2008 saw much turbulence in the financial markets, it is not surprising that the residuals, e, contain non-trivial individual information.

We also run the panel ECM test separately for different CDS maturities and industries. The results are provided in Appendix A. Consistently, we find the positive loadings on $\Delta y_{r_i,t,\tau}$ (not reported to save space) and negative loadings on $e_{i,t-j,\tau}$. The results support our previous argument that the residuals contain only transient information and all individual CDSs converge to the respective fitted CDS curves over time.

Table 4: Year-by-Year Panel Error Correction Model and CDS Convergence Test

This table reports the CDS convergence test using the error correction model. The sample period is from May 2002 to May 2012. We run the error correction model (Equation (7)) for each year. We only report the β_2 coefficient (the loading on $e_{i,t-j,\tau}$) to conserve space. Model 1 reports the results for 5-day time difference and Model 2 reports the results for 20-day time difference. t-statistic is reported in square brackets. ***, **, and * denote, respective, statistical significance at the 1%, 5%, and 10% levels.

	Model 1			Model 2			Dummies	
	β_2	Adj R-sqr	Obs	β_2	Adj R-sqr	Obs	Firm Sector	Year-Month
Y2002	-0.016***	0.02	85,369	-0.027***	0.07	72,455	Yes	Yes
	[-25.71]			[-24.04]				
Y2003	-0.018***	0.05	141,210	-0.077***	0.24	128,339	Yes	Yes
	[-71.62]			[-170.81]				
Y2004	-0.007***	0.03	217,123	-0.028***	0.12	203,133	Yes	Yes
	[-48.14]			[-100.10]				
Y2005	-0.007***	0.02	314,864	-0.021***	0.10	293,106	Yes	Yes
	[-40.22]			[-73.69]				
Y2006	-0.013***	0.02	390,680	-0.036***	0.05	373,290	Yes	Yes
	[-66.60]			[-113.28]				
Y2007	-0.005***	0.05	438,783	-0.017***	0.11	423,541	Yes	Yes
	[-34.68]			[-59.70]				
Y2008	0.001***	0.10	423,921	0.028***	0.19	415,593	Yes	Yes
	[5.29]			[51.85]				
Y2009	-0.022***	0.06	422,318	-0.091***	0.16	408,019	Yes	Yes
	[-77.48]			[-153.65]				
Y2010	-0.019***	0.07	441,800	-0.070***	0.15	432,824	Yes	Yes
	[-91.81]			[-181.26]				
Y2011	-0.015***	0.05	432,428	-0.051***	0.14	422,277	Yes	Yes
	[-88.33]			[-181.48]				
Y2012	-0.006***	0.02	174,218	-0.012***	0.08	169,500	Yes	Yes
	[-20.65]			[-26.51]				

5 Convergence Speed

The ECM results in the previous section suggest that individual CDS spreads tend to converge to the respective fitted CDS curves over time, since the loadings on the residuals are all negative and statistically significant. In this section, we further investigate the speed of this convergence. We define the convergence speed, s,

$$s_{i,t,\tau} = \log \frac{|h_{i,t,\tau} - y_{r_i,t,\tau}|}{|h_{i,t-j,\tau} - y_{r_i,t,\tau}|},\ j = 5 \text{ or } 20 \text{ days}, \tag{8}$$

where $h_{i,t,\tau}$ is the time t, τ-maturity CDS-implied hazard rate from Equation (4) for firm i, and $y_{r_i,t,\tau}$ is the time t, τ-maturity hazard rate for the rating r to which firm i belongs. Here, we assume $y_{r_i,t,\tau}$ is the converged value of $h_{i,\cdot,\tau}$ from time $t-j$ to t. Therefore, if the distance between $h_{i,t,\tau}$ and $y_{r_i,t,\tau}$ (i.e. $|h_{i,t,\tau} - y_{r_i,t,\tau}|$) is smaller than the distance between $h_{i,t-j,\tau}$ and $y_{r_i,t,\tau}$ (i.e. $|h_{i,t-j,\tau} - y_{r_i,t,\tau}|$), it means h is approaching y from time $t-j$ to t. If $|h_{i,t,\tau} - y_{r_i,t,\tau}|$ is larger than $|h_{i,t-j,\tau} - y_{r_i,t,\tau}|$, it means h is moving away from y. In addition, the smaller the ratio, $\frac{|h_{i,t,\tau} - y_{r_i,t,\tau}|}{|h_{i,t-j,\tau} - y_{r_i,t,\tau}|}$, the faster is the convergence speed. After taking natural logarithm of the ratio, the convergence speed is interpreted as follows:

$$s_{i,t,\tau} \begin{cases} < 0, & h \text{ is approaching } y \text{ (convergence);} \\ = 0, & h \text{ is neither approaching nor moving away from } y; \\ > 0, & h \text{ is moving away from } y \text{ (divergence).} \end{cases} \tag{9}$$

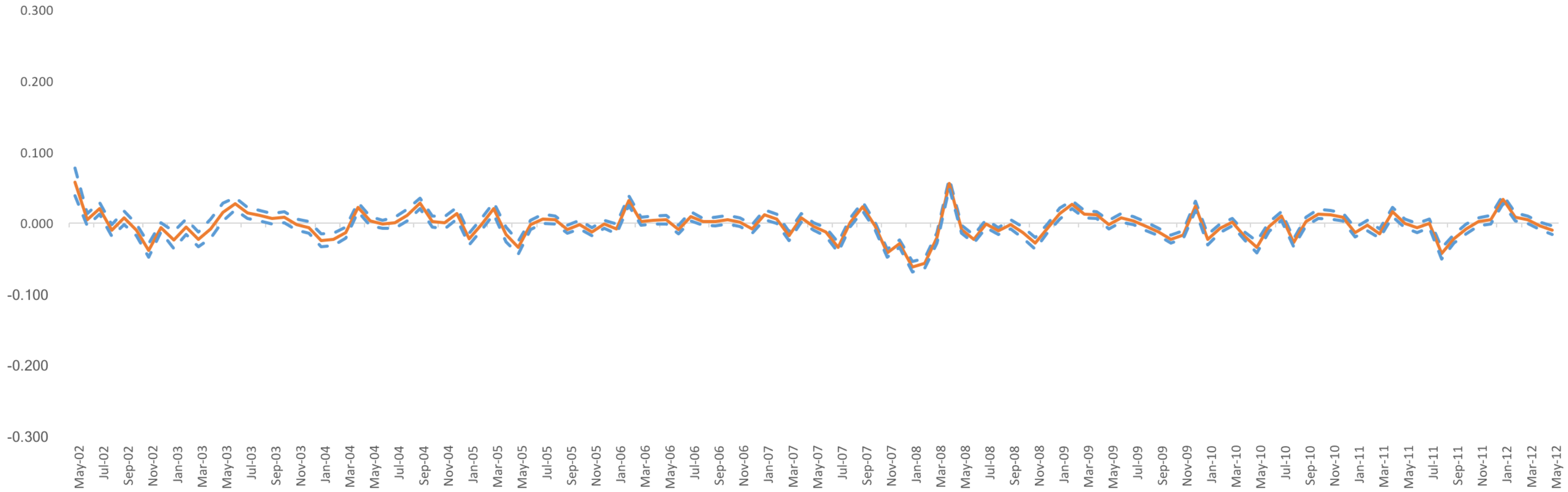
More importantly, the more positive $s_{i,t,\tau}$ value indicates h is moving faster away from y, while the *more negative* $s_{i,t,\tau}$ value indicates h is approaching *faster* towards y.

We use all the daily observations in a month to calculate s_m, the average $s_{i,t,\tau}$, and their 95% confidence intervals for that month.[10] Figure 3 plots the monthly convergence speed for j = 5 and 20 days. Not surprisingly, we find a mixed level of convergence speed over the sample period and s_m is particularly volatile during the 2008 financial crisis.

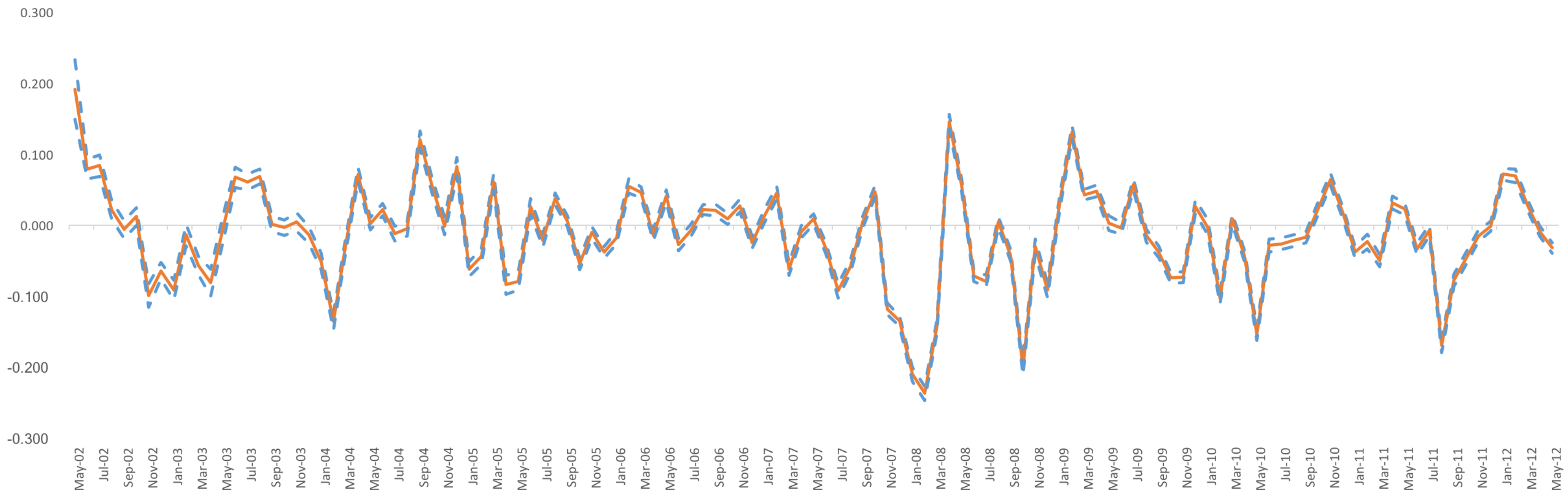
[10] Specifically, the 95% confidence interval $CI_{95\%} = s_m \pm 1.96 \times \frac{s_s}{\sqrt{n}}$, where s_m is the monthly average convergence speed in month m, and s_s, and n are, respectively, the standard deviation and the number of daily $s_{i,t,\tau}$ in that month.

Figure 3: Monthly Average Convergence Speed from May 2002 to May 2012

This figure plots the monthly average convergence speed for the 5-day and 20-day time difference. The dash lines indicate the 95% confidence interval.



(i) Average Convergence Speed (5 Days)



(ii) Average Convergence Speed (20 Days)

Next, we conjecture that the convergence speed may depend on the magnitude of the deviation ($|e_{i,t-j,\tau}|$): if $h_{i,t-j,\tau}$ is close to $y_{r_i,t-j,\tau}$, the propensity to converge may be weaker, whereas the propensity to converge may be stronger for a larger deviation between $h_{i,t-j,\tau}$ and $y_{r_i,t-j,\tau}$. In addition, we use the relative deviation ($e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$) to remove the scale of y and to prevent undue influence of outliers. To test our hypothesis, we sort our daily $s_{i,t,\tau}$ into five portfolios, based on their past relative deviations, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$: portfolio 1 consists of the most negative $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$ and portfolio 5 consists of the most positive $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. According to our hypothesis, we expect portfolio 1 and 5 to converge faster than portfolio 2 and 4, and we expect portfolio 3 to be the least likely to converge. We repeat the previous procedure to produce the monthly average convergence speed for the five portfolios ($s_{p,m}, p = 1, 2, ..., 5$), according to Equation (8).

Table 5 reports, in Columns 1–5, the one-sided t-test results if the monthly average convergence speed is significantly less from zero for the five portfolios. Column 6 (Column 7) reports the paired t-test results if the convergence speeds of portfolio 1 (portfolio 5) is faster and more negative than portfolio 3. Panel A reports the results for 5-day time difference, while Panel B reports the results for 20-day time difference. It is clear that results for the 20-day difference are more stable and stronger, compared to those for the 5-day difference. Among the five portfolios, portfolio 5 with the most positive relative deviation has the most negative (or fastest) convergence speed. As predicted, the convergence speed is U-shape; portfolio 3 has the slowest convergence speed. Both portfolios 3 and 4 exhibit divergence, though the coefficients are not statistically different from zero.

Figure 4 plots the time series of monthly average convergence speed for portfolio 1, 3, and 5 for the 20-day time difference. The time-series plot clearly shows that portfolio 1 (the most negative relative deviation) and 5 (the most positive relative deviation) are much more likely to converge than portfolio 3. The convergence speed of portfolio 3 hovers around the x-axis at zero, meaning that the propensity of convergence is rather weak. Convergence speed for portfolios 1 and 5 is mostly negative. This figure, again, confirms our previous finding that the further h is away from y, the faster is the convergence speed. Therefore, the magnitude of the deviation affects the speed of the convergence. Interestingly, we also find that portfolio 5 does not converge (showing positive $s_{5,m}$) in 2007 and 2008. This corresponds with our previous

Table 5: Convergence Speed

This table reports the t-test results for the monthly average convergence speed of the five portfolios; portfolio 1 (5) consists of the most negative (positive) relative deviations. The sample period is from May 2002 to May 2012. Columns 1–5 test if the individual portfolio convergence speed is significantly less than zero (i.e. one-sided t-test), and Columns 6 (Column 7) reports the result of whether convergence speed of portfolio 1 (portfolio 5) is statistically faster than portfolio 3 (i.e. $s_{1,m}$ or $s_{5,m}$ is more negative than $s_{3,m}$). Panel A reports the results for 5-day time difference and Panel B reports the results for 20-day time difference. t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

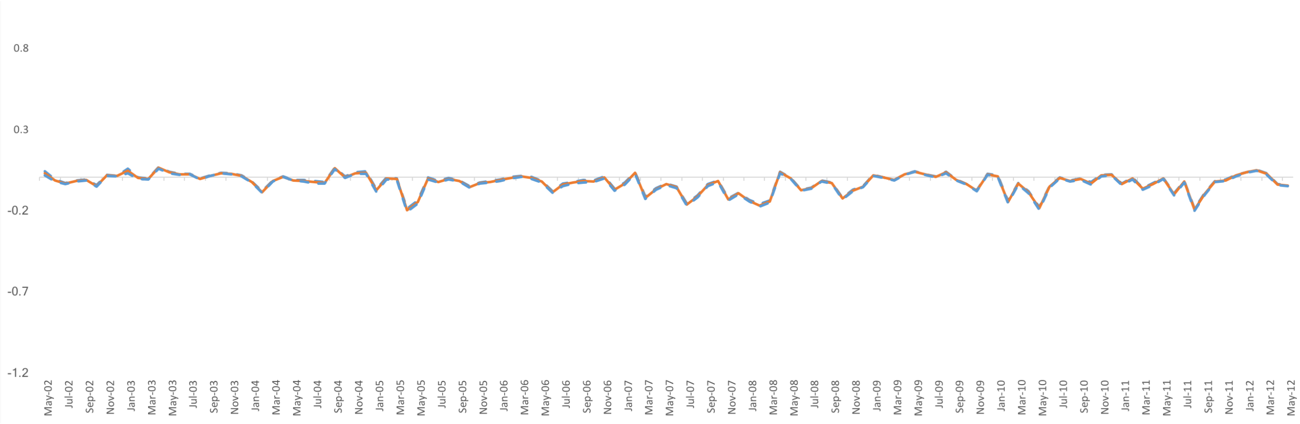
	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	[1] - [3]	[5] - [3]
Panel A: 5-day Time Difference (N = 121)							
$s_{p,m}$	-0.015***	-0.016***	-0.014***	0.061	-0.036***	0.000	-0.022*
t-stat	[-9.87]	[-5.78]	[-2.54]	[7.33]	[-3.70]	[-0.07]	[-1.48]
Panel B: 20-day Time Difference (N = 121)							
$s_{p,m}$	-0.034***	-0.032***	0.033	0.033	-0.105***	-0.068***	-0.138***
t-stat	[-6.72]	[-3.13]	[1.35]	[1.34]	[-3.97]	[-3.28]	[-2.85]

finding that β_2 coefficient is negative in year 2008 in our ECM results. A more comprehensive analyses on portfolio convergence are provided in Appendix B.[11]

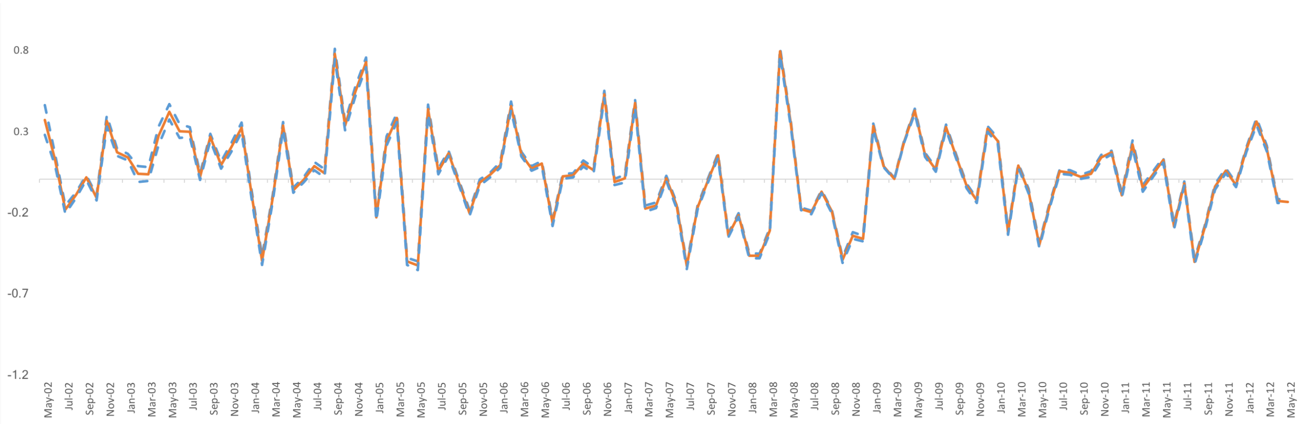
[11] We repeat the analyses using the absolute deviation ($|e_{i,t-j,\tau}|$). The results are qualitatively the same, but weaker.

Figure 4: Portfolio Monthly Average Convergence Speed (20-day Time Difference)

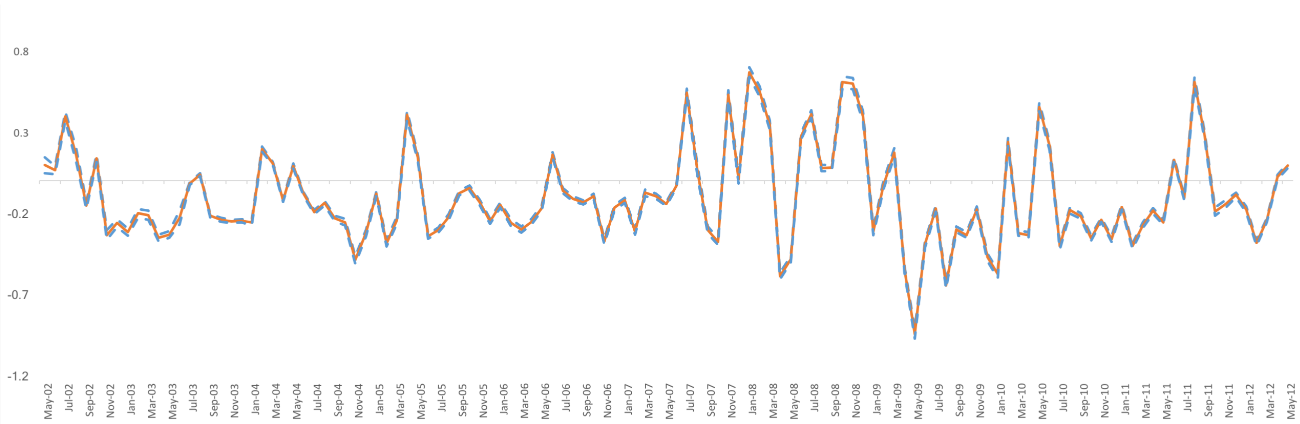
This figure plots the monthly average convergence speed, $s_{p,m}$ for portfolio 1, 3, and 5; portfolio 1 (5) consists of the most negative (positive) relative deviations. The sample period is from May 2002 to May 2012. The dash lines indicate the 95% confidence interval.



(i) Portfolio 1



(ii) Portfolio 3



(iii) Portfolio 5

6 Trading Strategy Exploiting the Convergence Speed

The convergence results in the previous section suggest a potential profit-making opportunity. Since we observe a significantly negative loading on $e_{i,t-j,\tau}$ in our ECM analysis, we can predict the future movement of the individual CDS spreads. Define the 5- or 20-day holding-period return of the CDS spreads as:

$$r_{i,t,\tau} = \frac{CDSSpr_{i,t,\tau}}{CDSSpr_{i,t-j,\tau}} - 1,\ j = 5 \text{ or } 20 \text{ days.} \tag{10}$$

One can expect a positive holding period return if one buys a CDS with a negative $e_{i,t-j,\tau}$ at time $t-j$ and sell that CDS at time t when the CDS spread moves up from time $t-j$ to t. Likewise, in the case of a positive $e_{i,t-j,\tau}$, a positive holding period return can be expected if one shorts a CDS with a positive $e_{i,t-j,\tau}$ at time $t-j$ and buy back that CDS at time t, as the CDS spread moves down from time $t-j$ to t. Moreover, since the larger deviation between h and y has a stronger tendency to converge, more profit per trade is expected if one trades between the most negative $e_{i,t-j,\tau}$ and the most positive $e_{i,t-j,\tau}$. Unfortunately, we are not able to perform a true transaction-based profitability test, because the CDS spread in Markit is a composite spread produced from the average quotes.[12] So instead of trading individual CDSs, we simply long/short the CDS portfolios in Section 5 to average out the influence of individual CDSs and their bid-ask spreads. Recall that portfolio 1 has the most negative $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$ and portfolio 5 has the most positive $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$, hence our trading strategy is to hold portfolio 1 while shorting portfolio 5. The two portfolio positions are unwind j days later.

Table 6 reports the holding period return for the five portfolios and the long-short strategy above. Panel A reports the returns for 5-day holding period and Panel B reports the returns for 20-day holding period. As expected, we find positive holding period return for portfolio 1 (3.2% and 8.2%, respectively, for 5- and 20-day cases), and negative holding period return for portfolio 5 (-0.4% and -0.8%, respectively, for 5- and 20-day cases). More importantly, we find the holding period returns monotonically decreases from portfolio 1 to 5, with the long-short

[12]Our Markit database contains CDS spreads expressed as composite prices instead of bid and ask prices. Most CDS databases provide composite prices for CDS; only GFI provides actual traded prices, but its data coverage is comparatively small. See Mayordomo, Peña, and Schwartz (2014) for a comprehensive comparison of the mainstream CDS databases.

strategy producing 3.6% and 9%, respectively for the 5- and 20-day holding periods.

When examining at the yearly breakdown, we find that, for most years, portfolio 1 produces the most positive holding period returns while portfolio 5 produces the most negative holding period returns. The difference between portfolio 1 and 5 is significantly at the 1% level for every year from 2002 to 2012. However, we note that portfolio 5 has a very large positive return in 2008 (2.9% and 13%, respectively, for 5- and 20-day holding periods). The positive returns indicate that portfolio 5 did not experience a convergence in 2008, and that the abnormal positive loadings in the ECM analysis for that year is largely due to portfolio 5. We also perform the portfolio return analyses based on CDS maturities and underlying sectors, and we find similar results. The details are provided in Appendix C. For robustness check, we repeat our portfolio return analyses, using past deviation ($e_{i,t-j,\tau}$). We find our conclusions still hold; we indeed observe positive profit, albeit the profit is slightly smaller. The detailed results are available upon request.

Table 6: Portfolio Holding Period Returns

This table reports the portfolio returns for 5- and 20-day holding periods. The sample period is from May 2002 to May 2012. The individual holding period return is defined as $r_{i,t,\tau} = CDSSpr_{i,t,\tau}/CDSSpr_{i,t-j,\tau} - 1, j = 5$ or 20 days. Each day, we sort the calculated returns into 5 portfolios, according to the relative deviation from its fitted CDS curve, $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Portfolio 1 has the most negative $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$ while portfolio 5 has the most positive $e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$. Columns 1–5 report the average returns for the five portfolios and the last column reports the difference between portfolios 1 and 5. The t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	[1] - [5]
Panel A: 5-day Holding Period						
Y2002–2012	$\boxed{0.032}$	0.011	0.004	0.000	$\boxed{-0.004}$	0.036***
						[45.39]
Y2002	0.031	0.008	0.003	0.014	0.018	0.013***
						[2.70]
Y2003	0.003	-0.009	-0.013	-0.016	-0.021	0.025***
						[9.87]
Y2004	0.024	0.005	-0.006	-0.014	-0.015	0.039***
						[16.97]
Y2005	0.047	0.020	0.009	0.000	-0.004	0.050***
						[22.83]
Y2006	0.027	0.007	-0.001	-0.006	-0.012	0.039***
						[25.82]
Y2007	0.045	0.026	0.015	0.011	0.003	0.041***
						[19.87]
Y2008	0.071	0.040	0.035	0.034	$\boxed{0.029}$	0.043***
						[14.66]
Y2009	0.016	-0.006	-0.016	-0.020	-0.021	0.036***
						[13.66]
Y2010	0.037	0.009	0.004	0.000	-0.009	0.046***
						[17.88]
Y2011	0.027	0.014	0.011	0.005	-0.002	0.028***
						[17.45]
Y2012	0.012	-0.003	-0.003	-0.005	-0.004	0.017***
						[5.09]
Panel B: 20-day Holding Period						
Y2002–2012	$\boxed{0.082}$	0.033	0.018	0.007	$\boxed{-0.008}$	0.090***
						[47.69]
Y2002	0.109	0.036	0.034	0.070	0.089	0.019
						[1.33]
Y2003	-0.036	-0.053	-0.048	-0.067	-0.087	0.051***
						[10.95]
Y2004	0.029	-0.002	-0.022	-0.041	-0.051	0.080***
						[16.93]
Y2005	0.117	0.057	0.033	0.016	-0.005	0.122***
						[36.09]
Y2006	0.046	0.004	-0.015	-0.025	-0.040	0.086***
						[32.80]
Y2007	0.155	0.092	0.062	0.040	0.030	0.125***
						[30.00]
Y2008	0.265	0.173	0.164	0.160	$\boxed{0.130}$	0.135***
						[19.17]
Y2009	0.016	-0.033	-0.061	-0.069	-0.076	0.092***
						[13.31]
Y2010	0.082	0.026	0.012	-0.004	-0.030	0.112***
						[18.30]
Y2011	0.072	0.048	0.038	0.025	0.002	0.070***
						[19.66]
Y2012	0.015	-0.019	-0.019	-0.022	-0.018	0.033***
						[6.21]

7 Information Content of CDS Curves and their Residuals

In this section, we study and compare the information content of the individual CDSs, the fitted fitted CDS curves, and the fitted residuals. We choose a collection of firm-specific and systematic factors that were shown to explain CDS spread in previous studies,[13] and we run the pooled regression below:[14]

$$CDSSpr_{i,t,\tau} = \beta_0 + \beta_1 FirmSpecific_{i,t} + \beta_2 Systematic_t + \varepsilon_{i,t,\tau} \quad (11)$$

where $CDSSpr$ is the individual CDS spreads, $FirmSpecific$ is a vector of variables related to firm-specific risks of CDS spreads, and $Systematic$ is a vector of variables related to systematic risks of CDS spreads. We use Equation (11) as a benchmark and perform two further pooled regressions with the dependent variables $y_{r_i,t,\tau}$ and $e_{i,t,\tau}$, respectively, in order to investigate the information content of the fitted implied curves and the residuals. In addition, we use firm sector dummies and year-month dummies to control for the sector and time fixed effects in the pooled regressions. In Table 7, Panels A and B report the summary statistics for the firm-specific credit and liquidity variables, and Panel C reports the summary statistics for the market condition variables. The definition of the variables are detailed in Appendix D. Interestingly, the average HL (the highest-minus-low of CDS spreads within one month) is 36 bps, and the standard deviation is 145 bps. The maximum HL is 22,849 bps. It means that CDS spread can suddenly move up dramatically in a very short time in respond to the near credit event. Some CDSs are not traded actively or they are traded only when credit quality of the underlying has changed; therefore, the fluctuations of the CDS spreads could be large.

Table 8 reports the factor correlation coefficients. As expected, the correlation between

[13] The factors tested are chosen from, for example, Lin, Kolokolova, and Poon (2016), Subrahmanyam, Tang, and Wang (2014) and Tang and Yan (2013). The list of factors includes firm's credit risk factors (such as cash ratio, profitability, accounting leverage, firm size, credit rating, historical stock volatility), liquidity proxies (such as Amihud stock illiquidity, number of contributors to CDS quotes, days of zero CDS returns, high-minus-low, Amihud measure of CDS, and Roll covariance measure, and the first principal component of all the aforementioned illiquidity measures), market variables (such as 5-year swap rate, difference between 5- and 2-year Treasury notes, difference between Baa and Aaa yields, and VIX), and cross-sectional CDS medians and means. See Appendix D for more details.

[14] We include CDS maturity in our pooled regression since individual firm has multiple CDS spreads with different maturities.

Table 7: Variable Descriptive Statistics

This table reports the mean, standard deviation, maximum, and minimum of the variables used in the panel regression. The sample period is from May 2002 to May 2012. The number of observations is 3,658,096. CR is the cash ratio, Profit is firm's accounting profitability, Lev is firm's accounting leverage, and Size is firm's accounting total asset. Rating is the averaged rating across rating agencies, ranging from 1 (AAA rating) to 7 (C rating). HVol is the underlying firm's stock historical volatility. EqIllq is the Amihud (2002) measure of the underlying stock, Contr is the number of contributors to the CDS quotes, Zeros is the proportion of the zero returns in one month, HL is the difference between highest and lowest CDS spreads in one month, Amihud is the Amihud (2002) measure using the CDS spreads, and Roll is the Roll (1984) measure using the CDS spreads. Recovery is the reported CDS recovery rate. Swap is the U.S. 5-year swap rate, and Slope is the difference between 5-year and 2-year Treasury notes. BaaAaa is the spread between Baa and Aaa yields. VIX is the CBOE VIX index. The detailed definition of the variables is provided in Appendix D.

	Mean	Std	Max	Min
Panel A: Credit Variables				
CR	0.485	0.634	15.784	0.000
Profit	0.172	0.705	1.697	-12.532
Lev	0.646	0.202	4.530	0.139
Size ($'000)	23,638	46,553	786,035	5
Rating	4.133	1.086	7.000	1.000
HVol (%)	4.759	4.525	57.584	0.000
Panel B: Liquidity Variables				
EqIlliq	0.799	26.948	1,347.484	0.000
Contr	6.016	3.237	27.000	2.000
Zeros	0.152	0.256	1.000	0.000
HL (bp)	35.954	148.583	22,848.561	0.000
Amihud	0.006	0.005	0.143	0.000
Roll	0.000	0.003	0.362	0.000
Panel C: Market Condition Variables				
Recovery (%)	39.389	2.672	75.000	7.500
Swap	3.433	1.353	5.760	0.970
Slope	-0.727	0.552	0.180	-1.660
BaaAaa	1.200	0.554	3.500	0.570
VIX	21.850	10.340	80.860	9.890

CDS spreads and fitted hazard rates (y), and that between CDS spreads and residual (e) are huge. The correlation coefficients are 62% and 63%, respectively. We also observe high correlation between CDS spreads and firm-specific CDS liquidity factors, e.g. the correlation coefficients with high-minus-low of the CDS spreads and Roll liquidity measure are 78% and 54%, respectively.

Table 9 reports the benchmark regression results. Here CDS spread is used as the dependent variable. Model 1 includes only firm-specific credit risks. The adjusted R-squared is just 17%. All factors are significant at the 1% level. The loadings on $Profit$ and $Size$ are negative as expected. A higher profitability leads to lower default risk. Larger firms are known to have lower default risk, as they have more capital and borrowing capacity to buffer business shocks. Interestingly, we observe positive loading on cash ratios. This finding is consistent with the precautionary motive of cash holdings. Subrahmanyam, Tang, and Wang (2014) and Tang and Yan (2013) find that CDS spread has a positive relationship with firm's cash ratio. They argue that firms become more concerned about their default risk when CDSs are written on them, because the information implied by CDS spreads may affect their debt renegotiation. Therefore, these firms tend to hold more cash when CDS spread increases. Model 2 reports the regression results for the firm-specific credit risks based on market information such as stock return, volatility, and credit rating. The adjusted R-squared is 25%, slightly higher than Model 1. The results is reasonable since, compared with the more static accounting-based variables in Model 1, CDS spreads respond to changes in market variables more rapidly. Again, all loadings are significant at 1% level. The loading on $Rating$ is positive, meaning that worse rating increases CDS spreads. We observe negative loading on historical stock volatility. The finding might be due to the precautionary motive induced by future uncertainty mentioned above. However, the correlation between historical volatility and CDS spreads is rather low at -2%.

Table 8: Variable Correlation

This table reports the correlation (in percentage) among the dependent variables (CDSSpr) and the regressors. The sample period is from May 2002 to May 2012. CDSSpr is the CDS spreads; y and e are the components of the Nelson-Siegel model. CR is the cash ratio, Profit is firm's accounting profitability, Lev is firm's accounting leverage, and Size is firm's accounting total asset. Rating is the averaged rating across rating agencies, ranging from 1 (AAA rating) to 7 (C rating). HVol is the underlying firm's stock historical volatility. EqIllq is the Amihud (2002) measure of the underlying stock, Contr is the number of contributors to the CDS quotes, Zeros is the proportion of the zero returns in one month, HL is the difference between highest and lowest CDS spreads in one month, Amihud is the Amihud (2002) measure using the daily CDS spreads, and Roll is the Roll (1984) measure of the CDS spreads. Recovery is the reported CDS recovery rate. Swap is the U.S. 5-year swap rate, and Slope is the difference between 5-year and 2-year Treasury notes. BaaAaa is the spread between Baa and Aaa yields. VIX is the CBOE VIX index. The detailed definition of the variables is provided in Appendix D. The variables are (1) CDSSpr, (2) y, (3) e, (4) CR, (5) Profit, (6) Lev, (7) Size, (8) Rating, (9) HVol, (10) EqIllq, (11) Contr, (12) Zeros, (13) HL, (14) Amihud, (15) Roll, (16) Recovery, (17) Swap, (18) Slope, (19) BaaAaa, and (20) VIX.

	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)	61.69	62.62	-1.20	-17.16	25.52	-10.01	40.56	-2.45	2.09	-12.78	-0.89	78.24	2.51	54.05	-45.61	-13.99	-12.89	26.01	23.14
(2)		-20.01	-1.53	-29.54	30.93	-17.90	67.05	-2.81	10.80	-20.20	6.49	42.11	-3.30	28.02	-26.55	-22.16	-19.09	44.99	40.29
(3)			0.32	6.55	2.94	4.13	-11.94	-0.12	-7.45	2.44	-7.04	51.90	5.52	37.73	-20.84	3.27	1.64	-11.26	-9.58
(4)				-6.55	-33.52	-7.05	0.38	2.55	1.56	-13.77	12.55	-3.08	-2.02	-0.95	-3.52	-2.83	-0.85	-4.19	-3.92
(5)					-37.61	7.19	-34.75	11.11	-5.28	7.86	-6.98	-9.34	2.99	-5.92	9.23	-2.11	-0.38	-0.61	0.25
(6)						-3.28	32.11	-9.41	-3.08	0.81	-4.55	16.77	3.17	10.52	-13.30	-3.50	-4.70	4.81	4.29
(7)							-40.55	7.94	-1.50	6.26	-12.36	-3.95	7.58	-3.07	1.66	-5.75	-3.26	0.86	1.96
(8)								-14.55	5.72	-16.39	14.41	21.82	-2.52	15.03	-18.28	4.08	4.98	0.05	-1.35
(9)									-2.83	-1.57	0.86	0.69	3.55	0.00	4.71	0.90	-1.22	22.60	16.15
(10)										-2.11	-0.52	0.95	0.46	1.00	1.88	-1.40	-1.96	2.87	2.12
(11)											-24.13	-3.37	-13.62	-5.40	6.70	31.95	24.91	-10.36	-13.74
(12)												-4.48	-10.90	-1.75	1.55	31.62	15.05	-2.95	-7.09
(13)													11.93	66.01	-39.07	-7.07	-8.44	22.16	19.61
(14)														15.94	-5.45	-16.99	-15.42	3.55	5.59
(15)															-24.67	-4.57	-5.84	12.75	10.36
(16)																7.06	6.42	-4.67	-2.33
(17)																	63.45	-30.34	-40.34
(18)																		-23.48	-37.78
(19)																			80.98

Model 3 reports the regression results using firm-specific illiquidity proxies. Interestingly, we observe a rather high explanatory power: the adjusted R-squared is 65%, and most of the variables have regression coefficients that are significant at the 1% level. This finding is consistent with Corò, Dufour, and Varotto (2013) and Tang and Yan (2007), in which the authors find CDS illiquidity to significantly impact on the CDS spreads. $Contr$ and $Zeros$ are related to the trading volume of CDSs. When CDS is less frequently traded, the CDS spreads tend to be higher; hence, we observe negative loading on $Contr$ and positive loading on $Zeros$. Similarly, *Amihud* is also related to the trading volume and price impact, and we observe a negative loading on *Amihud*. Both HL and *Roll* are proxies for CDS bid-ask spreads. Again, we find positive loadings on these two factors. The findings are consistent with the previous studies in which CDS bid-ask spread, or CDS illiquidity in general, is reported to be positively related to CDS spreads. Model 4 tests CDS recovery rate and maturity. The adjusted R-square is 30%, and all factors are significant at 1% level. The loading on *Recovery* is negative, as a higher recovery rate should lead to a lower CDS spread. The loading on $Maturity$ is positive, indicating that, on average, CDS spreads is higher for CDSs with longer time to maturity. Model 5 reports the results for variables representing systematic risks. The R-square is 11%. Both the median and the average of the CDS spreads are positively significant at the 1% level, indicating that the peer CDSs provide pricing information for the individual CDS, consistent with the theoretical model of Cespa and Foucault (2014). Finally, we find a positive loading on *Slope*, which is statistically significant at the 5% level. Slope is the different between 5- and 2-year Treasury notes. *Slope* reflects the liquidity preference, as long-term investors expect a premium for giving up liquidity. A positive loading for *Slope* indicates that a tightening of cash liquidity will increase CDS spread.

Model 6 reports the regression results for all the factors combined. The overall adjusted R-square is 73%. The significance and the signs remain the same for most factors. We only observe $Size$ and $Zeros$ experienced a sign change possibly due to multicollinearity; both regression coefficients are very small.

Next, we investigate how the Nelson-Siegel fitted component, y, and residual, e, are related to these factors that drive CDS spreads. In order to answer this question, we run the same regression in Equation (11), but we use the rating-based hazard rate (y) and the residual (e)

Table 9: Panel Regression on CDS Spreads

This table reports the panel regression results for CDS spreads. The sample period is from May 2002 to May 2012. Detailed variable definitions are provided in Appendix D. t-statistics is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Dependent = $CDSSpr$					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.004***	-0.031***	0.017	0.231***	0.005***	0.057
	[-10.85]	[-90.01]	[0.00]	[585.82]	[5.80]	[0.01]
CR	0.003***					0.001***
	[116.02]					[63.64]
Profit	-0.003***					0.000***
	[-116.47]					[26.82]
Lev	0.036***					0.010***
	[397.68]					[179.94]
Size	-0.000***					0.000***
	[-172.29]					[77.69]
Rating		0.012***				0.006***
		[850.15]				[620.93]
Hvol		-0.000***				-0.000***
		[-40.72]				[-24.66]
EqIllq			-0.000			-0.000
			[-0.00]			[-0.00]
Contr			-0.001***			-0.000***
			[-220.92]			[-92.79]
Zeros			0.001***			-0.001***
			[29.40]			[-19.33]
HL			1.546***			1.287***
			[1732.30]			[1529.04]
Amihud			-0.602***			-0.209***
			[-296.40]			[-99.58]
Roll			0.612***			0.639***
			[125.73]			[148.59]
PC1			0.000			0.000
			[0.00]			[0.00]
Recovery				-0.523***		-0.175***
				[-988.67]		[-482.90]
Maturity				0.001***		0.000***
				[204.36]		[12.01]
Swap					0.000	-0.000***
					[1.23]	[-3.66]
Slope					0.001**	0.001***
					[2.15]	[5.58]
BaaAaa					-0.000	-0.005***
					[-0.71]	[-34.08]
VIX					-0.000	-0.000***
					[-1.36]	[-8.82]
MedCDS					0.800***	0.889***
					[112.53]	[129.54]
AvgCDS					0.326***	0.022***
					[66.00]	[7.93]
Firm Section Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sqr	0.17	0.25	0.65	0.30	0.11	0.73
Obs	3,658,096					

as dependent variable, respectively, in order to examine the information content of these two components. Table 10 reports the regression results for the rating-based hazard rate (y). As before, Model 1 to Model 5 reports the results for the different sets of factors, and Model 6 reports the results for all the factors combined. Similar to results in the benchmark regression reported in Table 9, we find all the significant cases and the signs of the regression coefficients are the same as before. Moreover, we observe an even higher explanatory power. Specifically, we observe a much higher explanatory power in the regression of credit risk as well as systematic risk factors, but a lower explanatory power in the regression using liquidity factors. This finding indicates that the fitted CDS curves fully capture the important credit and liquidity information in the individual CDS spread, and that the Nelson-Siegel separation helps to filter out the transient and noise in individual CDS spreads. Overall, the results suggest that the rating-based hazard rate fully capture the majority of the priced risks in individual CDS spreads.

We then run the pooled regression for the residuals (e). The results are reported in Table 11. When all factors are included (Model 6), the adjusted R-square is just 42%. Among Model 1 to Model 5, Model 3 which includes only liquidity factors has the highest explanatory power, while other models have little explanatory power. The results suggest that the residual e contains largely transient illiquidity and noise.

We repeat the analyses above on different industry sectors, subsample periods, and CDS maturities. We find similar results in terms of factors' explanatory power, and all the significant cases and conclusion are consistent with our main findings discussed above. In summary, the results for rating-based hazard rate exhibit much higher explanatory power than those for the residuals. A summary of the goodness-to-fit of all these additional regressions is reported in Table 12. The detailed results are available upon request.

Table 10: Panel Regression on Rating-Based Hazard Rate (y)

This table reports the panel regression results for the rating-based hazard rate (y). The sample period is from May 2002 to May 2012. Detailed variable definitions are provided in Appendix D. t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Dependent = y					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	0.008***	-0.062***	0.029	0.150***	0.007***	-0.052
	[23.02]	[-252.00]	[0.00]	[348.41]	[8.11]	[-0.01]
CR	0.002***					0.000***
	[95.92]					[21.59]
Profit	-0.009***					-0.002***
	[-405.99]					[-145.24]
Lev	0.038***					0.008***
	[445.50]					[142.16]
Size	-0.000***					0.000***
	[-421.36]					[286.27]
Rating		0.022***				0.020***
		[2209.32]				[1874.86]
Hvol		-0.000***				-0.000***
		[-103.17]				[-98.92]
EqIllq			0.000			0.000
			[0.00]			[0.00]
Contr			-0.001***			-0.000**
			[-242.80]			[-2.45]
Zeros			0.011***			0.004***
			[157.72]			[85.60]
HL			0.765***			0.338***
			[585.54]			[383.21]
Amihud			-0.854***			-0.120***
			[-287.03]			[-54.67]
Roll			0.289***			0.243***
			[40.55]			[53.86]
PC1			0.000			-0.000
			[0.00]			[-0.00]
Recovery				-0.311***		-0.075***
				[-537.17]		[-197.97]
Maturity				0.001***		0.000***
				[281.85]		[20.23]
Swap					-0.000	-0.000***
					[-1.52]	[-3.96]
Slope					0.000	0.000**
					[1.16]	[2.45]
BaaAaa					-0.001**	-0.000*
					[-2.50]	[-1.85]
VIX					0.000	0.000***
					[0.49]	[5.94]
MedCDS					0.913***	0.666***
					[128.02]	[92.49]
AvgCDS					0.825***	0.741***
					[166.61]	[250.56]
Firm Section Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sqr	0.41	0.69	0.40	0.33	0.29	0.76
Obs	3,658,096					

Table 11: Panel Regression on Residuals (e)

This table reports the panel regression results for the residuals (e). The sample period is from May 2002 to May 2012. Detailed variable definitions are provided in Appendix D. t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Dependent = e					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-0.009***	0.018***	0.000	0.119***	0.005***	0.061
	[-21.94]	[41.88]	[0.00]	[241.00]	[4.68]	[0.01]
CR	0.002***					0.002***
	[73.93]					[69.33]
Profit	0.005***					0.003***
	[173.64]					[126.42]
Lev	0.015***					0.009***
	[142.51]					[106.32]
Size	0.000***					-0.000***
	[105.96]					[-84.85]
Rating		-0.004***				-0.009***
		[-230.72]				[-536.31]
Hvol		0.000***				0.000***
		[29.57]				[52.59]
EqIllq			0.001			0.001
			[0.00]			[0.00]
Contr			-0.000***			-0.000***
			[-4.05]			[-88.68]
Zeros			-0.009***			-0.005***
			[-125.18]			[-75.85]
HL			1.237***			1.359***
			[935.67]			[1017.47]
Amihud			-0.054***			-0.126***
			[-17.85]			[-37.80]
Roll			0.727***			0.767***
			[100.78]			[112.43]
PC1			-0.001			-0.001
			[-0.00]			[-0.00]
Recovery				-0.280***		-0.027***
				[-424.79]		[-46.62]
Maturity				0.000***		0.000***
				[27.70]		[3.40]
Swap					0.000**	-0.000
					[2.45]	[-0.51]
Slope					0.000	0.001***
					[1.08]	[3.06]
BaaAaa					-0.000	-0.006***
					[-1.06]	[-28.51]
VIX					-0.000**	-0.000***
					[-2.22]	[-11.09]
MedCDS					0.498***	0.813***
					[61.57]	[74.65]
AvgCDS					-0.375***	-0.692***
					[-66.76]	[-154.70]
Firm Section Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sqr	0.04	0.04	0.35	0.07	0.02	0.42
Obs	3,658,096					

Table 12: Panel Regression by Year, Maturity, and Industry

This table reports the adjusted R-squared for different panel regressions. The sample period is from May 2002 to May 2012. We repeat the panel regression (Equation (11)) on CDS spreads, rating-based hazard rates (y), and residuals (e) for CDS maturities, sample years, and the industry classification of the underlying, respectively, and their regression R-squares are reported. Panel A reports the regression results by year, Panel B reports the regression results by CDS maturity, and Panel C reports the results by industry.

	Adj R-sqr			Dummies		
	$CDSSpr$	y	e	Firm Sector	Year-Month	Obs
Panel A: Year						
Y2002	0.66	0.79	0.57	Yes	Yes	92,717
Y2003	0.67	0.84	0.54	Yes	Yes	151,414
Y2004	0.71	0.79	0.55	Yes	Yes	233,004
Y2005	0.66	0.77	0.36	Yes	Yes	332,317
Y2006	0.66	0.78	0.29	Yes	Yes	410,211
Y2007	0.69	0.80	0.35	Yes	Yes	460,646
Y2008	0.79	0.84	0.48	Yes	Yes	442,840
Y2009	0.76	0.79	0.52	Yes	Yes	441,700
Y2010	0.64	0.84	0.20	Yes	Yes	462,287
Y2011	0.75	0.77	0.36	Yes	Yes	448,294
Y2012	0.80	0.78	0.48	Yes	Yes	182,666
Panel B: Maturity						
6M	0.72	0.66	0.38	Yes	Yes	308,245
1Y	0.75	0.70	0.47	Yes	Yes	468,378
2Y	0.73	0.74	0.46	Yes	Yes	471,722
3Y	0.74	0.77	0.45	Yes	Yes	506,898
4Y	0.77	0.80	0.47	Yes	Yes	359,003
5Y	0.74	0.80	0.43	Yes	Yes	544,392
7Y	0.74	0.81	0.41	Yes	Yes	504,271
10Y	0.73	0.81	0.39	Yes	Yes	495,187
Panel C: Industry						
Basic Materials	0.61	0.80	0.37	No	Yes	288,110
Consumer Goods	0.78	0.79	0.40	No	Yes	676,253
Consumer Services	0.77	0.80	0.48	No	Yes	644,278
Energy	0.78	0.75	0.43	No	Yes	362,034
Financials	0.74	0.89	0.82	No	Yes	68,717
Healthcare	0.73	0.74	0.45	No	Yes	280,143
Industrials	0.74	0.76	0.52	No	Yes	610,072
Technology	0.78	0.85	0.53	No	Yes	329,538
Telecom Services	0.76	0.84	0.67	No	Yes	87,147
Utilities	0.68	0.88	0.55	No	Yes	290,499

8 Conclusion

In this paper, we use the individual senior unsecured tier CDS spreads of U.S. firms from May 2002 to May 2012 to construct daily rating-based CDS curves using the Nelson-Siegel model. We show that the empirical fitted CDS curves have good properties.

Results from error correction model (ECM) estimation show that the residuals (e) over 5- and 20-day differences are transient. Moreover, the larger the deviation is, the faster the CDS spread will converge to the fitted curve. Hence, by taking a long position in the portfolio of CDSs with the most negative deviation and a short position in the portfolio of CDSs with the most positive deviation, one can generate an average profit of 3.6% (9%) for the 5-days (20-day) holding period. All the results are robust in terms of subsample periods, CDS maturities, and industries, as the conclusion is qualitatively the same.

We then investigate the information content of the CDS spreads, the rating-based hazard rates (y), and the residuals (e). We find that the rating-based hazard rate (y) is highly correlated to all the factors known to explain CDS spreads, while the residuals (e) are mainly driven by transient illiquidity factors and noise. A slightly higher R-square is observed for y than the individual CDS spreads. This finding suggests that component y is effective in the sense that it subsumes the CDS risk factors efficiently.

Our findings highlight the economic substance of rating-based CDS curves, given the evidence of convergence of CDS spread towards the fitted curve over time, and the important information content of the fitted curves. Given these curves provide CDS spreads or implied hazard rates for all CDSs across rating classes and maturities, they are potentially very useful in credit risk management. We also show a profit-making trading opportunity for exploiting the deviations from the CDS curves.

References

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets 5*, 31–56.

Bongaerts, D., F. Jong, and J. Driessen (2011). Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market. *Journal of Finance 66*, 203–240.

Carr, P. and L. Wu (2011). A simple robust link between American puts and credit protection. *Review of Financial Studies 24*(2), 473–505.

Cespa, G. and T. Foucault (2014). Illiquidity contagion and liquidity crashes. *Review of Financial Studies 27*, 1615–1660.

Collin-Dufresne, P., R. S. Goldstein, and J. S. Martin (2001). The determinants of credit spread changes. *The Journal of Finance 56*(6), 2177–2207.

Conrad, J., R. Dittmar, and A. Hameed (2011). Cross-market and cross-firm effects in implied default probabilities and recovery values. *Working Paper*.

Corò, F., A. Dufour, and S. Varotto (2013). Credit and liquidity components of corporate CDS spreads. *Journal of Banking & Finance 37*, 5511–5525.

Das, S., P. Hanouna, and A. Sarin (2009). Accounting-based versus market-based cross-sectional models of CDS spreads. *Journal of Banking & Finance 33*(4), 719–730.

Das, S. R. and P. Hanouna (2009). Hedging credit: Equity liquidity matters. *Journal of Financial Intermediation 18*, 112–123.

Doshi, H., J. Ericsson, K. Jacobs, and S. M. Turnbull (2013). Pricing credit default swaps with observable covariates. *Review of financial studies 26*(8), 2049–2094.

Finnerty, J. D., C. D. Miller, and R.-R. Chen (2013). The impact of credit rating announcements on credit default swap spreads. *Journal of Banking & Finance 37*(6), 2011–2030.

Galil, K., O. M. Shapir, D. Amiram, and U. Ben-Zion (2014). The determinants of CDS spreads. *Journal of Banking & Finance 41*, 271–282.

Hull, J., M. Predescu, and A. White (2004). The relationship between credit default swap spreads, bond yields, and credit rating announcements. *Journal of Banking & Finance 28*(11), 2789–2811.

Leland, H. E. and K. B. Toft (1996). Optimal capital structure, endogenous bankruptcy, and the term structure of credit spreads. *Journal of Finance 51*, 987–1019.

Lesmond, D. A., J. P. Ogden, and C. A. Trzcinka (1999). A new estimate of transaction costs. *Review of Financial Studies 12*, 1113–1141.

Lin, M.-T., O. Kolokolova, and S.-H. Poon (2016). Systematic and firm-specifc risks of CDS spreads: Credit and liquidity under scrutiny. *Working Paper*.

Longstaff, F. A., J. Pan, L. H. Pedersen, and K. J. Singleton (2011). How sovereign is sovereign credit risk? *American Economic Journal: Macroeconomics 3*(2), 75–103.

Markit (2012, June). *User Guide CDS & Bonds*. Markit.

Mayordomo, S., J. I. Peña, and E. S. Schwartz (2014). Are all credit default swap databases equal? *European Financial Management 20*, 677–713.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *Journal of Finance 29*, 449–470.

Micu, M., E. M. Remolona, and P. D. Wooldridge (2006). The price impact of rating announcements: Which announcements matter? *Working paper*.

Nelson, C. and A. Siegel (1987). Parsimonious modeling of yield curves. *Journal of business*, 473–489.

Norden, L. and M. Weber (2004). Informational efficiency of credit default swap and stock markets: the impact of credit rating announcements. *Journal of Banking & Finance 28*(11), 2813–2843.

Roll, R. (1984). A simple implicit measure of the effective bid-ask spread in an efficient market. *The Journal of Finance 39*(4), 1127–1139.

Subrahmanyam, M., D. Y. Tang, and S. Q. Wang (2014). Credit default swaps and corporate cash holdings. *Working paper*.

Tang, D. Y. and H. Yan (2007). Liquidity and credit default swap spreads. *Working Paper*.

Tang, D. Y. and H. Yan (2013). What moves cds spreads? *Working paper*.

A Appendix: Additional Test for ECM Results

In this section, we provide the CDS convergence results for different maturities and industries, using ECM specification in Equation (7). Table 13 reports the results for different CDS maturities and Table 14 reports the results for different industries.

Table 13: CDS Convergence by Maturity

This table reports the CDS convergence using the error correction model. The sample period is from May 2002 to May 2012. We repeat the error correction model (equation (7)) for different CDS maturities. We only report the β_2 coefficient (the loading on $e_{i,t-j,\tau}$). Model 1 reports the results for 5-day time difference and Model 2 reports the results for 20-day time difference. t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Model 1 (5-Day)			Model 2 (20-Day)			Dummies	
	β_2	Adj R-sqr	Obs	β_2	Adj R-sqr	Obs	Firm Sector	Year-Month
6M	-0.031***	0.04	285,912	-0.102***	0.14	256,130	Yes	Yes
	[-73.62]			[-133.45]				
1Y	-0.017***	0.05	445,080	-0.060***	0.13	425,250	Yes	Yes
	[-62.36]			[-109.05]				
2Y	-0.018***	0.06	449,475	-0.065***	0.15	432,359	Yes	Yes
	[-73.03]			[-130.79]				
3Y	-0.013***	0.06	484,095	-0.054***	0.14	468,327	Yes	Yes
	[-61.94]			[-120.89]				
4Y	-0.013***	0.05	343,285	-0.055***	0.13	332,711	Yes	Yes
	[-47.36]			[-93.93]				
5Y	-0.012***	0.05	520,496	-0.053***	0.12	504,311	Yes	Yes
	[-60.39]			[-123.25]				
7Y	-0.012***	0.05	481,678	-0.053***	0.12	466,226	Yes	Yes
	[-55.19]			[-111.02]				
10Y	-0.014***	0.04	472,693	-0.058***	0.11	456,763	Yes	Yes
	[-60.16]			[-120.43]				

Table 14: CDS Convergence by Industry

This table reports the CDS convergence using the error correction model. The sample period is from May 2002 to May 2012. We repeat the error correction model (Equation (7)) by industry. We only report the β_2 coefficient (the loading on $e_{i,t-j,\tau}$). Model 1 reports the results for 5-day time difference and Model 2 reports the results for 20-day time difference. t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

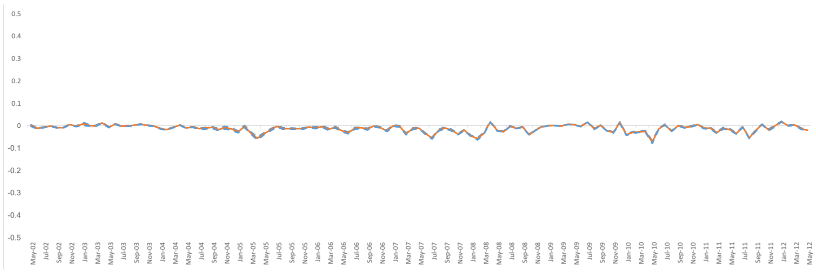
	Model 1 (5-Day)			Model 2 (20-Day)			Dummies	
	β_2	Adj R-sqr	Obs	β_2	Adj R-sqr	Obs	Firm Sector	Year-Month
Basic Materials	-0.011***	0.04	273,506	-0.030***	0.16	261,178	No	Yes
	[-53.54]			[-88.98]				
Consumer Goods	-0.018***	0.07	644,603	-0.082***	0.16	619,241	No	Yes
	[-80.99]			[-176.21]				
Consumer Services	-0.017***	0.06	614,689	-0.059***	0.16	590,911	No	Yes
	[-76.20]			[-133.34]				
Energy	-0.011***	0.13	345,310	-0.040***	0.28	332,339	No	Yes
	[-56.35]			[-100.12]				
Financials	-0.012***	0.06	65,662	-0.025***	0.26	63,565	No	Yes
	[-26.48]			[-38.84]				
Healthcare	-0.005***	0.09	265,932	-0.015***	0.23	252,949	No	Yes
	[-36.14]			[-62.54]				
Industrials	-0.016***	0.06	582,068	-0.058***	0.13	561,047	No	Yes
	[-70.91]			[-126.79]				
Technology	-0.019***	0.09	313,076	-0.105***	0.23	298,843	No	Yes
	[-58.80]			[-132.97]				
Telecom Services	-0.010***	0.03	82,260	-0.024***	0.10	78,754	No	Yes
	[-25.11]			[-37.11]				
Utilities	-0.032***	0.06	275,665	-0.075***	0.18	264,881	No	Yes
	[-72.26]			[-112.41]				

B Appendix: Portfolio Convergence Speed

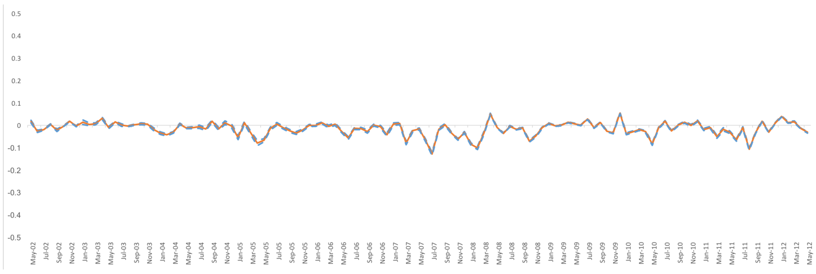
In this section, we provide the convergence speed for five portfolios. We sort our daily $s_{i,t,\tau}$ into five portfolios, based on their relative residuals, $e_{i,t-j,\tau}/y_{r_i,t,\tau}$. Portfolio 1 consists of the most negative $e_{i,t-j,\tau}/y_{r_i,t,\tau}$ and portfolio 5 consists of the most positive $e_{i,t-j,\tau}/y_{r_i,t,\tau}$. Figure 5 shows the portfolio convergence speed for 5-day time difference and Figure 6 shows the portfolio convergence speed for 20-day time difference.

Figure 5: Portfolio Convergence Speed (5-Day Difference)

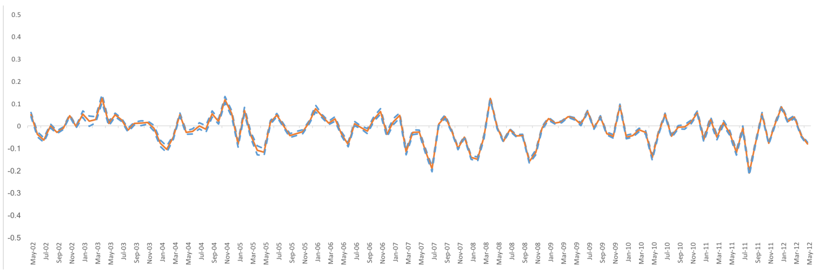
This figure plots the convergence speed for the five portfolios; portfolio 1 (5) consists of the most negative (positive) relative deviations. The sample period is from May 2002 to May 2012. The dash lines indicate the 95% confidence interval.



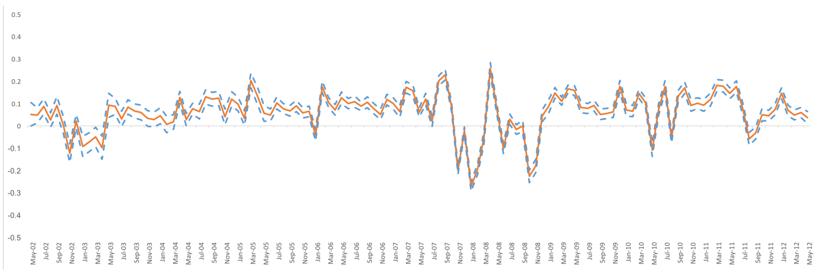
(i) Portfolio 1



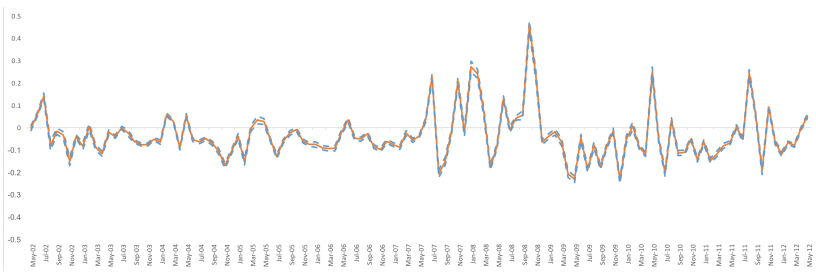
(ii) Portfolio 2



(iii) Portfolio 3



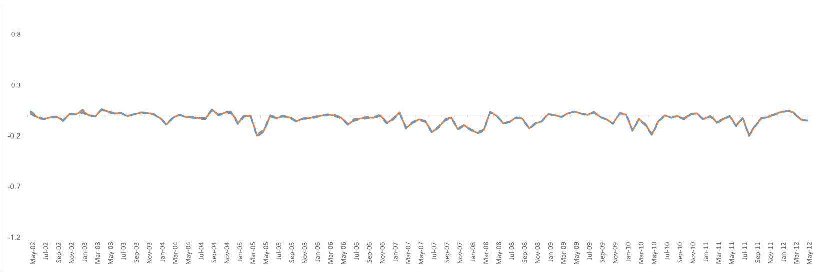
(iv) Portfolio 4



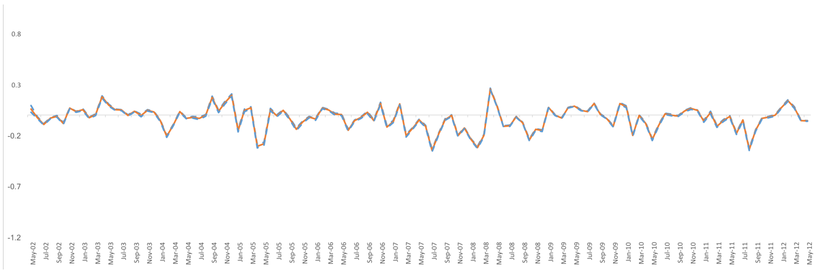
(v) Portfolio 5

Figure 6: Portfolio Convergence Speed (20-Day Difference)

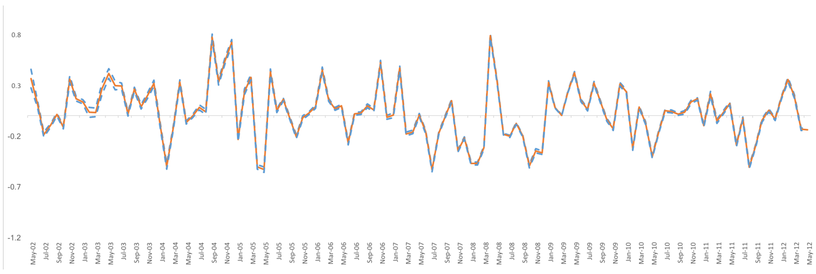
This figure plots the convergence speed for the five portfolios; portfolio 1 (5) consists of the most negative (positive) relative deviations. The sample period is from May 2002 to May 2012. The dash lines indicate 95% confidence interval.



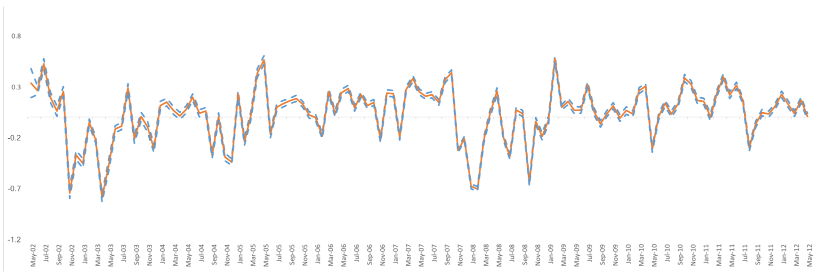
(i) Portfolio 1



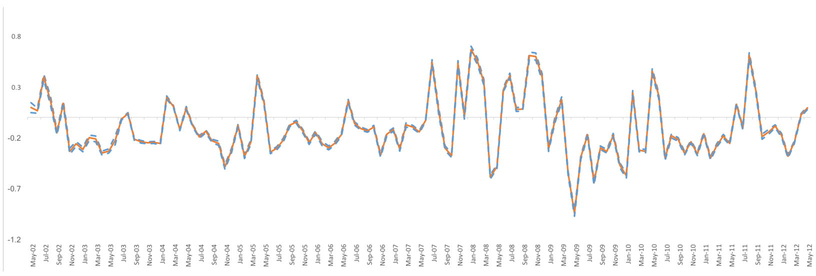
(ii) Portfolio 2



(iii) Portfolio 3



(iv) Portfolio 4



(v) Portfolio 5

C Appendix: Additional Trading Strategy Tests

In this section we provide the trading results for different maturities and industries, using the past relative deviation ($e_{i,t-j,\tau}/y_{r_i,t-j,\tau}$). Table 15 and 16 report, respectively, the portfolio returns for 5-day and 20-day holding periods.

Table 15: 5-Day Portfolio Returns by Maturity and Industry

This table reports the portfolio 5-day holding period returns for different CDS maturities and industries. The sample period is from May 2002 to May 2012. The individual CDS holding period return is defined as $r_{i,t,\tau} = CDSSpr_{i,t,\tau}/CDSSpr_{i,t-5,\tau} - 1$. Each day, we choose the CDSs with the same maturity (or the same industry), and sort the returns into five portfolios, according to $e_{i,t-5,\tau}/y_{r_i,t-5,\tau}$. Portfolio 1 contains the returns with the most negative $e_{i,t-5,\tau}/y_{r_i,t-5,\tau}$ while portfolio 5 contains the returns with the most positive $e_{i,t-5,\tau}/y_{r_i,t-5,\tau}$. Columns 1–5 report the average returns for the five portfolios and the last column reports the difference between portfolios 1 and 5. t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	[1] - [5]
Panel A: Maturity						
6M	0.107	0.043	0.018	-0.001	-0.016	0.123***
						[42.46]
1Y	0.056	0.027	0.010	-0.002	-0.009	0.065***
						[42.54]
2Y	0.029	0.015	0.005	-0.001	-0.005	0.033***
						[33.29]
3Y	0.018	0.009	0.004	0.000	-0.003	0.021***
						[25.78]
4Y	0.017	0.010	0.006	0.004	0.001	0.016***
						[20.29]
5Y	0.013	0.005	0.003	0.002	-0.002	0.014***
						[21.99]
7Y	0.013	0.006	0.003	0.002	-0.001	0.014***
						[21.03]
10Y	0.015	0.008	0.002	0.001	-0.001	0.016***
						[21.94]
Panel B: Industry						
Basic Materials	0.035	0.014	0.003	-0.001	-0.008	0.043***
						[25.98]
Consumer Goods	0.034	0.012	0.005	0.002	-0.005	0.039***
						[31.16]
Consumer Services	0.028	0.013	0.005	0.003	-0.005	0.033***
						[29.53]
Energy	0.032	0.011	0.003	0.001	-0.006	0.037***
						[24.77]
Financials	0.024	0.020	0.013	0.001	0.004	0.020***
						[5.98]
Healthcare	0.028	0.011	0.004	0.000	-0.007	0.035***
						[21.34]
Industrials	0.036	0.011	0.003	-0.002	-0.005	0.041***
						[28.66]
Technology	0.032	0.008	0.006	0.002	-0.008	0.040***
						[24.72]
Telecommunications Services	0.028	0.009	0.003	0.004	-0.006	0.035***
						[14.27]
Utilities	0.035	0.012	0.007	0.001	-0.003	0.038***
						[18.32]

Table 16: 20-Day Portfolio Returns by Maturity and Industry

This table reports the portfolio 20-day holding period returns for different CDS maturities and industries. The sample period is from May 2002 to May 2012. The individual CDS holding period return is defined as $r_{i,t,\tau} = CDSSpr_{i,t,\tau}/CDSSpr_{i,t-20,\tau} - 1$. Each day, we choose the CDSs with the same maturity (or the same industry), and sort the returns into five portfolios, according to $e_{i,t-20,\tau}/y_{r_i,t-20,\tau}$. Portfolio 1 contains the returns with the most negative $e_{i,t-20,\tau}/y_{r_i,t-20,\tau}$ while portfolio 5 contains the returns with the most positive $e_{i,t-20,\tau}/y_{r_i,t-20,\tau}$. Columns 1–5 report the average returns for the five portfolios and the last column reports the difference between portfolios 1 and 5. t-statistic is reported in square brackets. ***, **, and * denote, respectively, statistical significance at the 1%, 5%, and 10% levels.

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5	[1] - [5]
Panel A: Maturity						
6M	0.218	0.101	0.050	0.014	-0.027	0.245***
						[52.66]
1Y	0.126	0.066	0.034	0.006	-0.014	0.140***
						[47.92]
2Y	0.082	0.043	0.022	0.003	-0.009	0.091***
						[42.53]
3Y	0.059	0.030	0.016	0.007	-0.006	0.065***
						[34.02]
4Y	0.065	0.039	0.027	0.019	0.005	0.060***
						[31.29]
5Y	0.047	0.022	0.013	0.008	-0.004	0.051***
						[31.94]
7Y	0.044	0.023	0.012	0.011	-0.003	0.047***
						[32.97]
10Y	0.045	0.023	0.012	0.009	-0.002	0.047***
						[28.78]
Panel B: Industry						
Basic Materials	0.085	0.036	0.010	-0.001	-0.017	0.101***
						[35.66]
Consumer Goods	0.087	0.037	0.023	0.017	-0.009	0.097***
						[34.83]
Consumer Services	0.072	0.039	0.022	0.011	-0.008	0.080***
						[35.03]
Energy	0.074	0.032	0.015	0.010	-0.003	0.076***
						[21.14]
Financials	0.063	0.056	0.036	0.016	0.036	0.027***
						[3.67]
Healthcare	0.076	0.030	0.014	0.000	-0.016	0.092***
						[27.58]
Industrials	0.078	0.034	0.014	0.001	-0.008	0.086***
						[32.53]
Technology	0.086	0.029	0.030	0.008	-0.021	0.108***
						[30.38]
Telecommunications Services	0.063	0.026	0.012	0.009	-0.010	0.073***
						[16.12]
Utilities	0.084	0.038	0.035	0.010	-0.002	0.086***
						[19.29]

D Appendix: Explanatory Variables for CDS

In this section, we provide the description and the definition for the firm-specific and systematic CDS explanatory variables used in the panel regression.

Cash Ratio (CR): Firm's cash ratio determines the firm's solvency for debt due. If the firm has a higher cash ratio, the firm is more able to pay its debt. However, recent studies find that firms tend to increase cash holding for precautionary motive. (Subrahmanyam, Tang, and Wang (2014) and Tang and Yan (2013)). Cash ratio is calculated as [Cash + Short-term Investment]/[Current Liabilities].

Profitability (Profit): Firm's profitability is another determinant of firm's default risk. For firms with higher profits, they are less likely to default as they are more capable of paying outstanding debt. Different from cash ratio, which evaluates firm's short-term default risk, profitability is more related to the long-term propensity of default. We expect negative relationship between firm's profitability and its CDS spread. Profitability is calculated as firm's accounting retained earnings divided by its total assets.

Leverage (Lev): Higher level of leverage means the firm obtains its capital more from borrowing, thus raising the possibility of default. In this paper, we calculate firm's accounting leverage as total liabilities divided by total equity. We expect a positive relationship between leverage and CDS spread.

Size: Larger firms are less likely to default than small firms, since they have more capital as buffer against losses. We use the firm's total asset in their quarterly reports to proxy for size, and we expect a negative relationship between firm size and its default risk.

Rating: Rating reflects the overall firm's future perspectives in terms of solvency. We obtain the rating information via Markit. Markit calculates firm's average rating as the average of the Moody's and S&P ratings adjusted to the seniority of the CDS and rounded to not include the '+' and '-' levels.

Historical Volatility (HVol): Doshi, Ericsson, Jacobs, and Turnbull (2013) find that the historical volatility of the underlying stock has the predictive power for the changes in CDS spreads. A larger stock volatility means the firm has higher uncertainty in the future. Here we use the historical stock volatility calculated from daily stock returns over the past 12 months.

Equity Illiquidity (EqIllq): Das and Hanouna (2009) find stock illiquidity also affects the CDS spread. Hence, we use the Amihud (2002) measure of the underlying stock by $EqIllq = Mean\left(\frac{|r_t^S|}{P_t \times V_t} \times 10^6\right)$, where r^S is the daily stock return, P is the stock daily closing price, and V is the stock daily trading volume. We calculate the stock illiquidity using stock daily data over the past 12 months.

Number of Contributors to CDS quotes (Contr): Trading volume is related to market liquidity. When the trading volume is high, the market is more efficient and thus the level of illiquidity should be lower. Since our CDS spread is a composite price, there is no information on CDS trading volume; we use the number of contributors to the CDS quotes as a proxy for CDS trading volume, following Bongaerts, Jong, and Driessen (2011).

Days of Zero Returns (Zeros): Lesmond, Ogden, and Trzcinka (1999) use the number of days of zero returns as a proxy of security illiquidity. They argue that, when market is illiquid, the security price is less likely to move. Here we use the daily CDS spreads to calculate the individual Zeros as (# days with zero return/T), where T is the number of trading days in one month.

High-minus-Low (HL): We use the difference between highest and lowest prices of CDS spread in a particular period as a proxy for illiquidity. Larger HL indicates that the CDS spread is more volatile, or traded less frequently in that period. Here HL is calculated using daily CDS data over the past one month.

Amihud measure of CDSs (Amihud): We construct the Amihud illiquidity as $Amihud = Mean\left(\frac{|r_t^C|}{Contr}\right)$, where r^C is the daily return of the CDS spread over the past one year and $Contr$ is the number of contributors to the CDS quotes. We use $Contr$ as a proxy for trading volume.

Roll measure (Roll): Roll (1984) argues that the effective bid-ask spread of the prices can be measured by $2\sqrt{-cov}$, where cov is the serial covariance of the change in price. Here we calculate the individual CDS Roll measure for one month as $2\sqrt{-cov(\Delta C_t, \Delta C_{t-1})}$, where Δ is the operator of daily change and C is the CDS spread. In addition, the Roll measure is defined only when the serial covariance is negative; therefore, we replace the value with zero if the serial covariance is positive.

PC1: PC1 is the first principal component of all the illiquidity factors. We construct our PC1 based on EqIllq, Contr, Zeros, HL, Amihud, and Roll.

Recovery and Maturity: CDS's recovery rate is related to market conditions (Tang and Yan 2013). Here, we use Markit reported CDS recovery. In addition, we use CDS times to maturity (from 6 month to 10 year) to control for the maturity effect.

Swap Rate (Swap), Term Slope (Slope), and Baa-Aaa Spread (BaaAaa): Collin-Dufresne, Goldstein, and Martin (2001) and Doshi, Ericsson, Jacobs, and Turnbull (2013) find these market variables have explanatory power for the changes in credit spreads. We use the 5-year swap rate, the difference between 5-year and 2-year Treasury notes, and the spread between Baa and Aaa yields ($BaaAaa$) as proxies for the market conditions in bond and credit markets.

CBOE VIX Index (VIX): CBOE VIX index is used as a proxy for equity market condition. VIX is often used as a fear gauge and investors' sensitivity to investment.

Cross-Sectional Median and Mean of CDSs (MedCDS and AvgCDS): Galil, Shapir, Amiram, and Ben-Zion (2014) find that the median CDSs provide cross-sectional predictability for individual CDS spreads. Here we use the cross-sectional median and mean of the CDSs as proxies for CDS market conditions.